Essays in Macroeconomics

by

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Thesis submitted to the University of Warwick

in partial fulfillment for the degree of

Doctor of Philosophy
in Economics

Department of Economics

June 2016

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WARWICK

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Acknowledgments

Firstly, I would like to thank my supervisor Michael McMahon. He has mentored me since I was a first-year undergraduate as his personal tutee and lecturer, and throughout my research in the Ph.D. His enthusiasm and passion have been crucially motivational to me, even during the tough times. I appreciate all the time, effort and ideas he has put into making my time at Warwick stimulating and rewarding at a personal and professional level. In addition, Thijs van Rens as my second supervisor, has also contributed much to my development. His energy for the subject is contagious, and he devoted significant amounts of time and effort to teach me what good macroeconomics is.

Numerous members of the Department of Economics have been a source of excellent advice, support, and friendships. In particular, I am very thankful to Christina Ammon, Anna Baiardi, Adam Hutchinson, Irfan Qureshi, Laura Sochat, Andis Sofianos, Spyros Terovitis and Raghul Venkatesh. I also thank many other members of the Department for general support throughout the Ph.D. I have learnt much from Roberto Pancrazi and Jeremy Smith. I thank the EC201 Macroeconomics 2 team over the years, especially Timo Leidecker and Tony Liu, for the many stimulating discussions and reminding me not to forget to ask the big questions. I am also grateful to Mike Waterson for his confidence in me when I was still an undergraduate, and allowing to proceed directly to the Ph.D. programme.

I am thankful to the Bank of England's Monetary Assessment and Strategy Division for arranging the research visit. I have hugely benefited from many thought-provoking discussions with many in the Monetary Transmission Mechanism team, and especially the Strategy team – not only in terms improving the third chapter of this thesis, but also transforming how I look at macroeconomics.

I am grateful for useful comments from David Aikman, George Alessandria, John Barrdear, Susanto Basu, Francesco Bianchi, Natalie Chen, Mike Clements, Richard Harrison, Thomas Lubik, Dennis Novy, Roberto Pancrazi, Giorgio Primiceri, Valerie Ramey, Kate Reinold, Irfan Qureshi, Vincent Sterk, James Talbot, Konstantinos Theodoridis, Marija Vukotic, Matt Waldron and Mike Waterson, as well as participants of the Money, Macro and Finance 2013 conference, American Economic Association's 2014 Annual Meeting ISIR session, the Warwick Macro and International Economics workshop, the ESRC DTC 2014 Conference, the RES Junior Researcher Symposium and the MMF-York-Bank of England PhD workshop and various internal workshops at the Bank of England.

I acknowledge the Economic and Social Research Council, as well as the Department of Economics, for funding the research part of my Ph.D.

Lastly, I would like to thank my family for their encouragement and love. For my parents who raised me to have an endless curiosity. They have supported and encouraged me to pursue my passions. And most of all for Vania Esady who has lovingly and patiently stood by my side through the difficult final stages of the Ph.D. is greatly appreciated. Thank you.

Boromeus Wanengkirtyo

June 2016

Declarations

The first chapter is solely my own work.

The second chapter is co-authored with Michael McMahon. I performed the empirical work (the VAR analysis and stylised facts), which is the primary contribution of this chapter. The interpretation of the results were developed from joint discussions.

The third chapter is co-authored with Lien Laureys and Roland Meeks (both at the Bank of England). The paper was written when I was a visiting academic at the Bank of England. I estimated the models, and generated the optimal policy frontiers and tradeoff results. I obtained the idea for the tradeoffs summary statistics, which was then refined in joint discussions. Similarly, the interpretation of the results were developed during joint discussions. Any views expressed in the third chapter are solely those of the authors and so cannot be taken to represent those of the Bank of England or to state Bank of England policy. This chapter should therefore not be reported as representing the views of the Bank of England or members of the Monetary Policy Committee or Financial Policy Committee.

I declare that the material contained in this thesis has not been used or published before, and has not been submitted for another degree or at another university.

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June 2016

Abstract

Broadly, the first two chapters analyse two novel sources of economic fluctuations, and the last chapter quantifies how the traditional monetary policy tradeoffs is affected by a mandate to stabilise financial variables.

The first chapter focuses on the macroeconomic effects by variations in the range of available goods produced. Previous work that analysed the real effects of financial shocks only considered the effect on the production of existing goods. Firms can also invest into production lines of new goods. A credit contraction reduce investment into new products, leading to lower competition and higher markups. This decreases consumption demand, as well as lowering labour demand and wages, reducing household income. This amplifies the response of consumption to financial shocks (19% more volatile). The DSGE model is able to match the VAR impulse responses on the predicted channels.

The second chapter resurrects the question if improved business practices contributed to the Great Moderation. While previous studies only examine inventory management, we analyse the role of supply chain management on enhancing production coordination across firms. VAR counterfactuals suggest that improved business practices have dampened order volatility by 40-50%. We therefore determine that better business practices contributed a significant 20-25% of the Great Moderation.

The third chapter shows how a policy of 'leaning against the wind' affects the traditional monetary policy tradeoff. An estimated, modified Gertler and Karadi (2011) model is used to compute optimal monetary policy under commitment for a range of central bank objectives. The main findings are that increased regard for financial variables: (a) makes price stability increasingly costly in terms of output stabilisation; (b) raises the cost of output and inflation volatility, in reducing financial volatility; (c) depend crucially on the underlying disturbance, and on the financial variable that policy aims to stabilise.

Abbreviations

A-B	Arellano-Bond estimator
AIC	Akaike Information Criterion
AR	Auto-regressive
BGM	Bilbiie, Ghironi and Melitz (2012)
BLS	US Bureau of Labor Statistics
C&I	Commercial and Industrial (loans)
CAR	Capital Adequacy Ratio
CES	Constant Elasticity of Substitution
COMPASS	Central Organising Model for Projection Analysis and Scenario Simulation
CPI	Consumer Price Index
DSGE	Dynamic Stochastic General Equilibrium
EDI	Electronic Data Interchange
GDP	Gross Domestic Product
FEVD	Forecast Error Variance Decomposition
FG	Final Goods (inventories)
GHH	Greenwood, Hercowitz and Huffman (1988)
GMM	Generalised Method of Moments
HP	Hodrick-Prescott filter

HV	High Volatility period (1967-1978)
IRF	Impulse Response Function
JIT	Just-in-time
LATW	Leaning against the wind
LV	Low Volatility period (1982-1996)
M&S	Materials and Supplies (inventories)
MZ	McCarthy and Zakrajšek (2007)
NAICS	North American Industry Classification System
NBER	National Bureau of Economic Research
NBER-CES	NBER and U.S. Census Bureau's Center for Economic Studies
OLS	Ordinary Least Squares
PCE	Personal Consumption Expenditures
PPI	Producer Price Index
QCEW	BLS Quarterly Census of Employment and Wages
RBC	Real Business Cycle
RMSE	Root Mean Squared Error
SIC	Standard Industrial Classification
SVAR	Structural vector auto-regression
TFP	Total Factor Productivity
VAR	Vector auto-regression
VMI	Vendor Management Inventory
WIP	Work-in-progress (inventories)

Chapter 1

Competition Effects of Financial Shocks on Business Cycles

1.1 Introduction

> *"... almost all cyclical movements in output since 1973 are attributable to markup variations."*
>
> – Julio J. Rotemberg and Michael Woodford (1999)

Since the 2008-10 global financial crisis, there has been renewed interest into how shocks originating from the financial sector have effects on the real economy. However, the past literature have focused on the intensive margin of investment – the changes in production of existing goods. This paper instead investigates how a 'competition channel' can arise from the extensive margin of investment – changes in the range of available goods – as a novel transmission channel of financial shocks. I empirically and theoretically quantify how credit contractions can prevent firms investing into new product lines and reduce product market competition. Firms charge higher markups, impeding the recovery as goods are more expensive. This competition channel amplifies the initial financial shock by inducing a greater fall in consumption.

Firstly with a VAR, I establish empirically (like the past literature) that credit supply contractions lead to lower loan issuance and exhibit effects typical of demand shocks – reductions in output and inflation. But importantly, I also show that during tight credit conditions, the number of establishments fall and markups rise, consistent with the competition channel. Secondly, in order to quantify the amplification effect of competition, I build in a financial sector into the Bilbiie et al. (2012) endogenous product variety DSGE model. Writeoff shocks that reduces banks' loan-issuing capacity leads to an interaction of extensive margin of investment with countercyclical markups, resulting in the peak consumption response to financial shocks of 28% larger, and 19% more volatile. This implies that if the extensive margin and competition effects are not considered, one would over-attribute the cause of the real effects of credit supply shocks to the intensive margin of investment. The policy implication is that given competition takes time to recover, policymakers should note the greater market imperfections imply a lower natural level of output. They should take this into account in order not to over-estimate the amount of slack available and implement excessively stimulatory policies that leads to high inflation.

The transmission channel works as follows. I model a financial shock as an asset-writeoff shock to banks, representing an exogenous credit supply contraction.[1] The financial shock forces banks to deleverage and contract their credit supply. I abstract away from the adverse systemic risk effects on the broader financial system, and instead focus on the frictions this event creates in the real sector through competition. Firms cannot finance as much new product entries, and this reduces competition. Markups then rise, resulting in a fall of consumption demand due to higher prices. At the same time, the reduction in aggregate demand decreases labour demand and wages, leading to a fall in hours worked due to the substitution effect. This leads to a drop in household income, which exacerbates the fall in consumption demand. The DSGE model's prediction of the channels through the reduction in competition, rise in markups and the fall in real wages is confirmed by VAR evidence to a credit supply shock. The model with variable markups manages to track the path of the fall in consumption demand well, and matches the peak effect displayed in the VAR impulse response.

This paper is most closely related to two strands of literature. The first strand the endogenous product variety and firm entry literature. I adopt the ideas from Bilbiie et al. (2012) of product varieties and variable markups as a transmission mechanism in a standard RBC model. They are also the first to adopt a broader interpretation of products, rather than firms, in a business cycle setting. The new literature on endogenous product varieties has moved away from firm entry, as start-ups tend to be small and have little aggregate implications. However, the value of product cre-

[1] One interpretation is that it can represent the large asset writedowns banks suffered during the 2008-10 financial crisis. For example, in the period around the end of 2007, Citigroup wrote-down approximately $39 billion of assets, largely due to its exposure to sub-prime mortgages. This is very large proportion of its $120 billion of total equity capital. At the time, Citigroup was the largest bank in the United States by total assets.

ation is much more substantial. Note that 'product entry' does not necessarily mean research and development of new products (which tends to be long-term, and is not very cyclical). Kung and Bianchi (2015) instead emphasise 'technology diffusion' – where firms invest into producing new products which have been already invented, but will still affect competition. Henceforth, I will use the term 'products' and 'varieties' synonymously with technological diffusion. From the production-side, Bernard et al. (2010) document using 5-digit SIC manufacturing data that 10% of value-weighted production is new products, in a given year. At business-cycle frequencies, this adds up to around 40% of new products being produced, a significant amount. Interestingly, they also note that 94% of product additions occur within *existing* firms. From the consumption side, using barcode-level data, Broda and Weinstein (2010) show that 40% of a typical consumer's basket consists of products created in the last four years (roughly coinciding with the numbers from Bernard et al. (2010)). A similar literature on firm entry includes Bergin and Corsetti (2008), Lewis and Poilly (2012), Lewis and Stevens (2013) and others.

Also importantly for the competition channel, Broda and Weinstein (2010) show that net product creation is highly procyclical (a 1% increase in sales lead to a 0.35% increase in product creation). In addition, the procyclicality of net product creation is driven by gross creation, rather than product destruction. This is consistent with the idea that credit constraints affect firms' ability to finance entries, which in turn affect the economy's product base and competition. However, if we allow for an endogenous product destruction rate in response to credit contractions (for example, see Hamano and Zanetti (2015)), this would strengthen the channel here.

The empirical linkage between competition and markups naturally comes from the international trade literature, often from estimating the Melitz and Ottaviano (2008) model. For example, Chen et al. (2009) demonstrate that higher competition (proxied by import penetration) leads to lower prices and markups. Montero and Urtasun (2014) reports a more direct connection to markups using the Bank of Spain's credit registry data. They show a positive and statistically significant association between industry markups and a direct measure of market concentration, as well as a proxy of financial pressure. A review of the role of variable markups in business cycles can be seen in Rotemberg and Woodford (1999).

The second strand is the real effects of financial shocks. The paper is closely aligned, but from an extensive-margin perspective, to Jermann and Quadrini (2012). They document the cyclical properties of debt and equity financing flows, build a model that assigns a role for financing, and replicate simultaneously real aggregate variables and financial flows to see the role of financial shocks. The extensive margin is also complementary to Queralto (2014), who attempt to explain 'slow recoveries from financial crises', by supply-side effects through endogenous TFP growth by firm creation. Instead, I examine the demand-side effects occurring from changes in market structure. A complementary paper on the role of financial shocks on markups is Gilchrist et al. (2014). They have a framework that firms may wish to increase short term markups in order to boost cash flow when credit is tight. However, this only explains the high frequency fluctuations in markups, as they aim to explain inflation dynamics. This is contrary to the VAR evidence in the next section, which show a more sluggish response of markups to credit tightenings.

Related papers on financial shocks include Del Negro et al. (2011), Kiyotaki and Moore (2012) and Christiano et al. (2014). This line of literature should be differentiated to the financial accelerator models, where the financial sector acts as only an amplification or propagation mechanism of traditional supply or demand shocks, rather than a source of shocks on its own. These models include Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Carlstrom and Fuerst (1997), Bernanke et al. (1999) and many others.

The rest of the paper is structured as follows. Section 1.2 summarises the current empirical literature on the real effects of credit shocks, and documents the competition effect with a VAR. Section 1.3 outlines the DSGE model. Section 1.4 explains the theoretical results of the model. Section 1.5 quantitatively compares the theoretical predictions with the VAR results, and offers industry-level empirical evidence that the competition channel exists. Section 1.6 concludes.

1.2 The Real Effects of Credit Supply Shocks

In this section, I offer evidence that the competition channel operates in aggregate data, complementing the existing literature on the real effects of credit supply shocks.

1.2.1 Existing Literature

Two recent papers addressed the difficulty of separating out credit supply and demand movements, empirically documenting that credit supply shocks has significant real effects. Bassett et al. (2014) use the Federal Reserve's Senior Loan Officer Opinion Survey, and document that a one standard deviation tightening to a measure of lending standards leads to a substantial (0.75%) decline in output and the core lending capacity by banks fall by 4%. Becker and Ivashina (2014) use Compustat data to calculate when firms start switching from bank to public debt. Any firm that raises new debt must have a positive demand for external funds, eliminating credit demand effects. Changes in debt-issuance behaviour of substituting firms inform us about conditions of aggregate bank credit supply. Despite the sample only including large firms who have access to public debt markets, the index is strong predictor of the likelihood of raising bank debt for firms which have never issued a bond (out-of-sample firms).

In addition, it is also important that credit supply drives investment levels. In short, if firms easily find financing from other sources, then credit supply movements has no impact on realised investment (the Modigliani-Miller proposition). However, there is evidence that firms find it difficult and/or costly to substitute funds. Amiti and Weinstein (2013) use a comprehensive, matched lender-borrower dataset of all listed Japanese firms, to show that granular bank shocks account for a significant 40% of the fluctuations in aggregate lending and investment. Notably, they also find these shocks matter during normal times, and not just during crises. Kashyap et al. (1993) and Slovin et al. (1993) show that while there is some attempt at substitution during credit contractions, it is not enough to compensate fully, leading to significant effects on investment.

1.2.2 Competition Effects and Credit Supply

I use a VAR with seven variables: a credit supply indicator, commercial and industrial loans, a competition proxy and markups, alongside the standard macro variables of consumption, inflation and the Federal Funds Rate. The credit supply indicator is a measure of credit standards cs_t, from the Federal Reserve Loan Officer Opinion Survey (Bassett et al., 2014). I use an unanticipated bank credit supply tightening in the VAR, to see if it leads to reductions in competition and higher markups. The proxy for competition is the number of establishments, from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages. Establishments are defined as 'economic units' – which could be a farm, a factory, or a store – so this is a close enough proxy to the idea of production lines. Aggregate markups are imputed from the log-inverse of private business labour share, following Nekarda and Ramey (2013) and Rotemberg and Woodford (1999). Inflation is the Personal Consumption Expenditure deflator. I also include C&I loans l_t to gauge the severity of the credit supply shock on realised lending. Logarithms and the first-differencing is applied to all variables, except the credit standards index and the Federal Funds Rate. The sample is quarterly from 1990 to 2009.

The VAR has one lag, as suggested by the Schwarz-Bayesian Information Criterion. The results do not qualitatively change for higher order lag structure, and the results remain statistically significant in a VAR(2).[2] It is identified by a recursive Choleski scheme, with the order:

$$\mathbf{X}_t = [cs_t \; N_t \; \mu_t \; c_t \; \pi_t \; r_t \; l_t]'$$

[2]See Figure (A.5) in the Appendix.

In other words, the indicator of credit supply are ordered first, so it can affect all other variables contemporaneously, while C&I loans cannot. N is ordered before μ as the level of competition can affect current pricing decisions, but higher markups is unlikely to induce product entry within the same quarter. The ordering of the macroeconomic variables y, π and r is standard in recursively-identified VARs, for example Bernanke and Gertler (1995). Loans are ordered last as the Federal Funds Rate acts as the risk-free benchmark to the price of loans. The results are robust to various alternative ordering schemes, including when the loans are ordered before the other real variables, and when credit standards are ordered after the macro variables.[3]

Figure 1.1 plots the impulse responses to a one standard deviation shock to credit standards (equivalent to a bank credit supply contraction), which is as expected for an adverse demand shock. There is a statistically significant negative response on consumption and inflation, and importantly, C&I loans. Comparing with the VAR in Bassett et al. (2014), the magnitudes of consumption impulse responses (output in their paper), are consistent. Note that the result is robust to using output, instead of using consumption as the indicator of economic activity.[4] They use 'core lending capacity' as they aim to measure aggregate lending, which responds less than the IRF of C&I loans here. This is expected because C&I loans typically have higher risk weights than residential loans, so C&I loans are cut back more sharply during a credit contraction.[5] However, the more inter-

[3]See Figures (A.2) and (A.3) in the Appendix.

[4]See Figure (A.4) in the Appendix.

[5]For example, the standardised risk weight of loans secured by commercial real estate is 100%, while those secured by residential property is 35%.

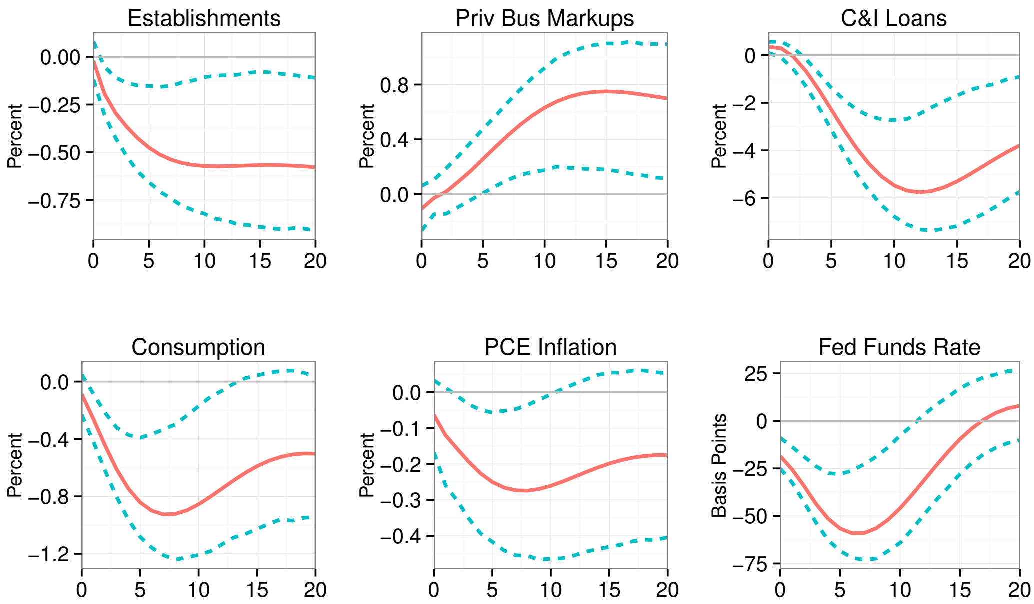

Figure 1.1. VAR Impulse Responses to a Credit Supply Contraction

Note: The credit contraction is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

esting variables are establishments and markups. Establishments slowly fall over time, and becomes statistically significant negative. Markups also fall but it eventually rises statistically significant above zero. In addition, the peak effect is close to the same horizon as the trough of establishments. This is consistent with the hypothesis that the rise is markups is due to competition effects.

Figure 1.2 plots the variance decomposition of three variables of interest, in response to credit supply shocks. Credit conditions is responsible a substantial 60% of the fluctuations in C&I loans, implying credit supply is an important determinant of overall loans extended. This is more than the FEVD of core lending capacity in Bassett et al. (2014), however, still within

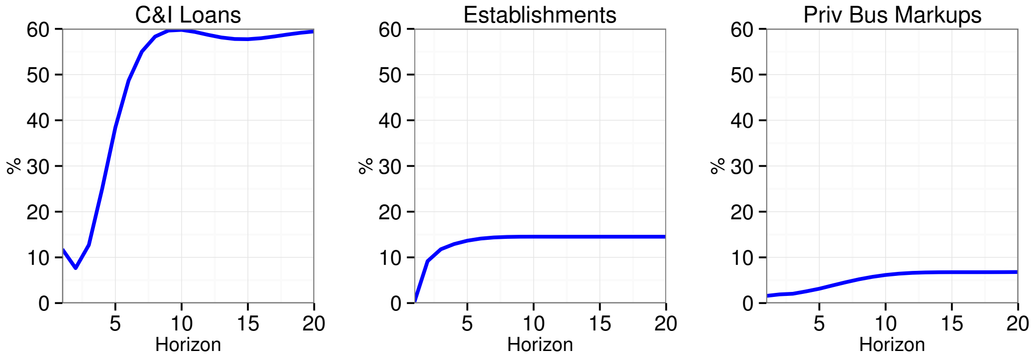

Figure 1.2. Forecast Error Variance Decomposition to credit supply shocks

Note: Each subplot shows the variance of the variable that is explained by shocks to credit standards cs_t, for a given horizon.

their bounds. In addition, a robustness check of using HP-filtered variables (in levels, instead of first-differenced), is closer to the 40% that they have.[6] Furthermore, credit supply shocks account for a non-negligible 15%, and 7% of the variation in establishments and private business markups, at business cycle horizons. Shocks to the number of establishments also explain another 6% of the variation in markups. They sound small, but their contributions are much larger than, say, monetary policy (demand) shocks which only accounts for a tenth of what credit supply shocks account for. These are also lower bound estimates – robustness checks using the level, HP-filtered variables suggest that credit supply shocks account for 20% of the variance of both establishments and markups. The results here further lend credibility to the mechanism from credit supply to competition and markups.

Lastly, the estimated DSGE literature such as Smets and Wouters (2007) find that exogenous price markup shocks are large and highly per-

[6]Also, this is notably similar to the result Amiti and Weinstein (2013) found using Japanese lender-borrower relationship data.

sistent. They account for 15% the fluctuations in GDP and 35-70% in inflation – both non-trivial amounts. Their model is also shown by Bils et al. (2012) to be inconsistent with product-level CPI micro data on reset price inflation. More specifically, the Smets and Wouters (2007) model predicts reset price inflation to be far too persistent. Competition effects can help resolve this. After an expansionary shock, competition increases and markups fall. This contributes to explaining why reset price inflation falls much faster after an expansionary shock, than actual inflation. However, I leave the implementation of this mechanism in an estimated medium-scale DSGE model for future research.

1.3 Model

This section describes the model built to explain the mechanism in a DSGE framework. I introduce a banking sector to the standard Bilbiie et al. (2012) (henceforth, BGM) real business cycle model with endogenous product varieties. I start with the description of the banking sector that finances the creation of new products, as this is the main modelling contribution. I then present the Kimball (1995) aggregator preferences as a microfoundation for variable markups, the agents in the economy and the equilibrium.

1.3.1 Banking Sector

The role of the bank is to provide loans, which finances the creation of new products. There is a single bank in the economy, which takes in deposits D_t from the households and has its own equity capital E_t. The bank's objective is – as would a firm that maximises shareholder value – to maximise the present discounted value of dividends DIV_t^B. The bank has no limits to how much loans L_t it issues, apart from a capital adequacy ratio. The loans it issues will eventually return back as deposits, so in this sense, it 'creates credit'. These loans L_t are the only assets that the bank has. On the liabilities side of the balance sheet are household deposits D_t and equity capital E_t, leading to the balance sheet identity $L_t = D_t + E_t$. The bank is capital constrained, so equity capital and the capital adequacy ratio determines the maximum amount of loans the bank issues.

$$CAR_t \leq E_t/L_t \tag{1.1}$$

Like the collateral constraint literature, I assume that the shocks are small enough that the constraint is binding at all times (in steady state, it binds, as writeoffs are positive).

Equity capital at the beginning of the period, evolves with the law of motion:

$$\mathbb{E}_t e_{t+1}\pi_{t+1}^c = e_t(1 - \mathbb{E}_t wr_t) + (i_t^L l_t - i_t^D d_t) - div_t^B - \frac{\kappa}{2}\left(\frac{l_t}{l_{t-1}} - 1\right)^2 l_t \tag{1.2}$$

where the lower case denotes the variables in real consumption goods terms (price index P_t and consumption inflation rate $\pi_t^c = P_t/P_{t-1}$). The term wr_t denotes the asset writeoff shock. Note the timing that banks do not know the realisation of the writeoff (which occurs at the end of the period) when they are making the decision to issue loans. The second term in brackets is the net interest payments the bank receives from its loan-making and deposit-taking operations. The third term is the dividends it pays to households, and the fourth term is loan adjustment costs.

The quadratic loan adjustment costs are in the style of De Nicolò et al. (2012), which captures the bank's information production costs about credit quality. This is the screening and monitoring per-unit costs when increasing lending, and per-unit liquidation costs when decreasing lending. This parameter will affect the persistence of the credit crunch, initially caused by the asset writeoff shock. I calibrate this parameter to match the persistence of loans to those observed in VAR impulse response.

Thus, the bank's objective is:

$$\max_{\{div_t^B, e_{t+1}, l_t\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t} div_t^B$$

subject to the capital adequacy requirement, the equity law of motion and the balance sheet identity. $\Lambda_{0,t}$ is the household's stochastic discount factor. The bank's optimality conditions are:

$$i_t^L - i_t^D = \psi_t \cdot CAR_t + \zeta_t \tag{1.3}$$

$$1 + \mathbb{E}_t wr_t = \mathbb{E}_t \frac{\Lambda_{t,t+1}}{\pi_{t+1}^c} \left[(1 + i_{t+1}^D) + \psi_{t+1} \right] \tag{1.4}$$

where $\zeta_t \equiv -\kappa \left(\frac{l_t}{l_{t-1}} - 1 \right) \frac{l_t}{l_{t-1}} - \frac{\kappa}{2} \left(\frac{l_t}{l_{t-1}} - 1 \right)^2 + \mathbb{E}_t \Lambda_{t,t+1} \kappa \left(\frac{l_{t+1}}{l_t} - 1 \right) \left(\frac{l_{t+1}}{l_t} \right)^2$ denotes the loan adjustment cost effects and ψ_t is the Lagrange multiplier on the capital adequacy ratio constraint, which reflects the scarcity of equity capital. Equation (1.3) is an equilibrium no-arbitrage condition reflecting how the spread of the equilibrium loan interest rate over the deposit interest rate (external funding cost) is an increasing function of the marginal value of equity. The writeoff shock will increase the scarcity value of equity, driving the rise in the loan interest rate. Equation (1.4) shows how the bank equates the marginal cost of investing into an extra unit of equity on the left hand side (the expected writeoffs), to the discounted marginal benefit of being able to issue more loans with a spread over its funding cost.

In steady state, equation (1.4) results $\psi = wr/\beta > 0$, where $wr > 0$ is the amount of steady state writeoffs, implying that the CAR constraint binds in steady state. This is equivalent to the standard financial friction models where there is probability of bank's capital being transferred to households, to ensure a financial constraint binds. Equation (1.3) implies that the steady state spread $i^L - i^D = \psi \cdot CAR$. From this, I can calibrate the steady state CAR and writeoffs (which determine ψ) to match average loan interest rate to the risk-free rate spread, and either observed CAR or writeoffs from the data.

1.3.2 Preferences

Kimball (1995) Aggregator

A crucial ingredient to the model is a micro-foundation for variable markups. The more conventional translog preferences from Feenstra (2003), adopted by BGM, has one parameter that pins down both the steady state markup and the elasticity of markups with respect to competition. However, the parameter that would match the steady state markup implied by estimated demand elasticities would result in a markup elasticity that is too small compared to the empirical estimates in Section A.2.1. Therefore, to achieve both steady state markup and markup elasticities that are empirically grounded, I use the Kimball (1995) consumption aggregator, with the functional form in Dotsey and King (2005) that has two parameters to pin the steady state markup and the markup elasticity.

The aggregator creates a smoothed-kinked (concave) demand curve. At the firm's normal relative share of production, it is easier to lose customers when it raises relative prices, as compared to gaining customers when lowering relative prices. An increase in competition, or the number of varieties, leads to a reduction in the relative share, as consumers value variety and spread their consumption over a larger number of varieties. This effectively shifts demand curve down for a subsidiary producing a particular variety, and more importantly for the channel, it faces a higher demand elasticity – lowering markups. The aim of Kimball (1995) is to use a more flexible demand function that creates another strategic complementarity that amplifies effects of nominal disturbances, to make a model of sticky prices plausible. The effect of the variable demand elasticity is countercyclical markups. Sbordone (2007) also uses this aggregator to investigate the effect of globalisation (i.e. a permanent increase in the number of varieties) on the slope of the Phillips curve. Other uses of the aggregator is in the macro pricing literature (Dotsey and King, 2005; Eichenbaum and Fisher, 2007; Levin et al., 2007; Vigfusson et al., 2009).

The household's expenditure minimisation problem with the Kimball aggregator and endogenous varieties is:

$$\min_{c_t(\omega)} \int_0^{N_t} p_t(\omega) c_t(\omega) d\omega \quad \text{subject to} \quad \int_0^{N_t} \Psi\left(\frac{c_t(\omega)}{C_t}\right) d\omega = 1, \qquad (1.5)$$

where $\Psi'(\cdot) > 0, \quad \Psi''(\cdot) < 0$. Full derivations can be found in the Appendix. I focus on the symmetric equilibrium (that all subsidiaries produce and charge the same price):

$$\int_0^{N_t} \Psi\left(\frac{c_t(\omega)}{C_t}\right) d\omega = 1 \Rightarrow N_t \Psi\left(\frac{c_t(\omega)}{C_t}\right) = 1 \tag{1.6}$$

Therefore, the relative share $x_t(\omega) \equiv c_t(\omega)/C_t = \Psi^{-1}\left(\frac{1}{N_t}\right)$ so typically the relative share x_t is not the market share $1/N_t$. The welfare-relevant price index P_t is:

$$P_t = \int_0^{N_t} p_t(\omega)\frac{c_t(\omega)}{C_t} d\omega = \int_0^{N_t} p_t(\omega)\Psi^{-1}\left(\frac{1}{N_t}\right) d\omega$$

Noting that in the symmetric equilibrium $p_t(\omega) = p_t(j)\ \forall i, j \in N$, so:

$$\begin{aligned} P_t &= p_t N_t \Psi^{-1}\left(\frac{1}{N_t}\right) \\ \rho_t &= \frac{p_t}{P_t} = \frac{1}{N_t \Psi^{-1}\left(\frac{1}{N_t}\right)} \end{aligned}$$

where ρ_t is the relative price, which can be thought as the ratio of the producer price index and the consumer price index. This relative price measure will be important for correctly deflating the welfare-relevant variables into the empirically relevant variables.

Dotsey and King (2005) Specification

The Dotsey-King specification is:

$$\Psi(x) = \frac{1}{(1+\eta)\gamma}\left[(1+\eta)x - \eta\right]^{\gamma} - \left[1 + \frac{1}{(1+\eta)\gamma}\right] \tag{1.7}$$

Dotsey and King (2005) highlights that a convenient property of this specification is that the Dixit-Stiglitz CES aggregator is a special case when $\eta = 0$. However, the counterfactual of 'no competition effects' will not be this due to discontinuities is the preferences when $\eta = 0$, causing different behaviour. I will instead use a parameterisation of $\eta < 0$ and γ that generates very low elasticities of markups with respect to varieties. The welfare-relevant aggregate price index can be written as:

$$P_t = \frac{1}{1+\eta}\left[\int_0^{N_t} p_t(\omega)^{\gamma/(\gamma-1)} d\omega\right]^{(\gamma-1)/\gamma} + \frac{\eta}{1+\eta}\int_0^{N_t} p_t(\omega) d\omega \tag{1.8}$$

The symmetric equilibrium implies that there is a common relative price to all varieties, $\rho_t(\omega) = p_t(\omega)/P_t$. It can be derived from rearranging:

$$P_t = \frac{1}{1+\eta}\left[N_t p_t^{\gamma/(\gamma-1)}\right]^{(\gamma-1)/\gamma} + \frac{\eta}{1+\eta} N_t p_t \tag{1.9}$$

$$1 = \frac{1}{1+\eta} N_t^{(\gamma-1)/\gamma} \rho_t + \frac{\eta}{1+\eta} N_t \rho_t \tag{1.10}$$

$$\rho_t = \frac{1+\eta}{N_t^{(\gamma-1)/\gamma} + \eta N_t} \tag{1.11}$$

As Sbordone (2007) noted, the literature does not offer much guidance for plausible values of η and γ. However, in this instance, there are two obvious calibration targets – the markup elasticity and steady state markups.

Firstly, using the derivations in the Appendix and the functional form, the elasticity of demand and desired markups are:

$$\theta_t = \frac{\Psi'(x_t)}{x_t \Psi''(x_t)} = \frac{\eta - (1+\eta)x_t}{(\gamma-1)(1+\eta)x_t} \tag{1.12}$$

$$\mu_t = \frac{\theta_t}{\theta_t - 1} = \frac{\eta - (1+\eta)x_t}{\eta - \gamma(1+\eta)x_t} \tag{1.13}$$

where the market share x_t is:

$$x_t = \Psi^{-1}\left(\frac{1}{N_t}\right) = \frac{1}{1+\eta}\left\{\eta + \left[(1+\eta)\gamma\left(\frac{1}{N_t}+1\right)+1\right]^{1/\gamma}\right\} \tag{1.14}$$

It can be clearly seen that markups are a function of the relative share x_t, which in turn is a function of the number of varieties N_t. This is the competition effect. Lastly, the elasticity of markups with respect to varieties (around the steady state) is composed of two components through the relative share x:

$$\frac{d\ln\mu}{d\ln N} = \frac{d\ln\mu}{d\ln x}\cdot\frac{d\ln x}{d\ln N} \tag{1.15}$$

$$\frac{d\ln\mu}{d\ln x} = \frac{\eta(\gamma-1)(1+\eta)x}{(\eta-(1+\eta)x)\,(\eta-\gamma(1+\eta)x)} \tag{1.16}$$

$$\frac{d\ln x}{d\ln N} = -\frac{1}{N\cdot x\cdot\Psi'(x)} = -\frac{1}{N\cdot x\cdot[(1+\eta)x-\eta]^{\gamma-1}} \tag{1.17}$$

where the time subscripts are omitted to show the variables are in steady-states. For parameter values in real space, there is no guarantee of a particular sign of the markup elasticity, or the steady state markup. Therefore, one has to be very careful on using the correct parameter space to achieve economically meaningful elasticities and steady state markups. The markup elasticity will be calibrated to values found in industry-level data, discussed in Section 1.5.

1.3.3 Independent Subsidiaries

Following BGM, there are monopolistically competitive independent subsidiaries $\omega \in [0, N_t]$ that produce one variety each. Therefore, I will refer to these variety producers as firms and subsidiaries interchangeably. Subsidiaries use labour, with production function $y_t(\omega) = Z_t h_t^C(\omega)$, where Z_t is an exogenous aggregate productivity shock and $h_t^C(\omega)$ is the labour input for a consumption-good producer ω.

Subsidiaries are owned by the parent firm, who they pass on their profits to as dividends:

$$div_t^S(\omega) = \left(\frac{\mu_t(\omega) - 1}{\mu_t}\right)\frac{C_t}{N_t} = \left(1 - \frac{1}{\mu_t}\right)\frac{C_t}{N_t} \tag{1.18}$$

where the last equality holds as we focus on the symmetric equilibrium. The preferences imply subsidiaries' optimal rule is to set relative prices to a markup $\mu_t = \theta_t/(\theta_t - 1)$ over marginal cost, so $\rho_t = \mu_t \cdot w_t/Z_t$.

1.3.4 Parent Firm

The parent firm is responsible for maintaining the product base in the economy. It shields the banking sector from defaults, as the product varieties fail randomly. This allows us to abstract away from default effects on the provision and demand of credit, and to focus on competition effects. Like banks, the parent firm maximises the expected present discounted value of dividends it pays to households. It receives profits from all subsidiaries, and pays back the loan it takes from the bank to finance the creation of new varieties N_t^E. The cost of each new variety is c_t^E, and varieties are destroyed at a rate δ. Therefore, the parent firm maximises:

$$\max_{\left\{div_t^P, N_{t+1}, N_t^E\right\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t} div_t^P \tag{1.19}$$

subject to:

$$div_t^P = N_t div_t^S - (1 + r_{t-1}^L) l_{t-1} \tag{1.20}$$

$$l_t = c_t^E N_t^E \tag{1.21}$$

$$N_{t+1} = (1-\delta)(N_t + N_t^E) \tag{1.22}$$

where $(1 + r_{t-1}^L) = (1 + i_{t-1}^L)/\pi_t^C$ is the real interest rate on loans. In other words, the dividends div_t^P is the leftover profits after servicing debt. It takes the real interest rate on loans and the cost of entry c_t^E as given. I assume that that new varieties can only be debt financed. This is reliant on the aforementioned stylised fact that firms find it difficult to substitute funds. Equation (1.22) is the law of motion for varieties, noting that the death shock δ also hits entrants, so only $(1-\delta)N_t^E$ entrants survive to produce next period.

This creates first order conditions very similar to BGM:

$$v_t = \mathbb{E}_t \Lambda_{t,t+1} \left[div_{t+1}^S + (1-\delta) v_{t+1} \right] \tag{1.23}$$

$$(1-\delta) v_t = \mathbb{E}_t (1 + r_t^L) c_t^E \tag{1.24}$$

where v_t is the Lagrange multiplier on the law of motion of varieties, or the value of a *new* variety. Equation (1.23) shows that the value of a variety is the present discounted value of the stream of dividends, accounting for product lifetime by the destruction rate δ. Equation (1.24) is reminiscent of the free-entry condition in BGM. It equates the value of a variety, conditional on survival to produce next period, to the expected cost of servicing the loan.

1.3.5 Upstream Suppliers

The upstream suppliers provides the parent firm with the infrastructure for a new variety to be produced (production line) to produce the new varieties. The sector only uses labour, so its production function is $N_t^E = Z_t \cdot \frac{h_t^E}{f^E}$. It is also exposed to the aggregate productivity shock, and f^E is only a scaling parameter that does not affect a first-order solution of the model. The sector operates under perfect competition, so entries are charged at marginal cost $c_t^E = \frac{w_t}{Z_t} \cdot f^E$.

1.3.6 Households

Households are fairly standard. There is a measure $[0, 1]$ of households, who consume an aggregated consumption good and supply labour $H_t = H_t^C + H_t^E$, where $H_t^C = N_t h_t^C$ is the total labour supply to the consumption goods sector, and H_t^E to the upstream suppliers. Following Gertler et al. (2012), the households have Greenwood et al. (1988) (hereafter, GHH) preferences with habit formation, and maximise:

$$\max_{\{c_t, h_t\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{1}{1-\sigma} \left[c_t - b \cdot c_{t-1} - \frac{\chi}{1+1/\varphi} H_t^{1+1/\varphi} \right]^{1-\sigma} \tag{1.25}$$

subject to:

$$c_t + d_t = (1 + r^D_{t-1})d_{t-1} + w_t H_t + div^B_t + div^P_t + wr_t e_t \tag{1.26}$$

where b is the degree of habit formation, $(1 + r^D_{t-1}) = (1 + i^D_{t-1})/\pi^C_t$ is the real interest rate on deposits, σ is the constant relative rate of risk aversion and φ is the Frisch elasticity of labour supply. The choice of GHH preferences is to get comovement between hours and real wages, which would be useful in replicating the empirical impulse responses later. Define:

$$U_t \equiv c_t - b \cdot c_{t-1} - \frac{\chi}{1 + 1/\varphi} H_t^{1+1/\varphi} \tag{1.27}$$

The first order conditions are:

$$MUC_t = U_t^{-\sigma} - \beta b \mathbb{E}_t U_{t+1}^{-\sigma} \tag{1.28}$$

$$MUC_t = \beta MUC_{t+1}(1 + r^D_t) \tag{1.29}$$

$$\chi H_t^{1/\varphi} = w_t \left[1 - \beta b \left(\frac{U_{t+1}}{U_t} \right)^{-\sigma} \right] \tag{1.30}$$

Equation (1.28) denotes the marginal utility of consumption. Equation (1.29) is the household's Euler equation for deposit savings, from which I derive the stochastic discount factor $\Lambda_{t,\tau} = \beta^{\tau-t} MUC_\tau / MUC_t$. Equation (1.30) is the household's labour supply equation.

1.3.7 Market Clearing and Exogenous Variables

The aggregate expenditure $P_t C_t = p_t y_t N_t$ can be rearranged for the output of the consumption goods sector, $C_t = \rho_t y_t N_t$. Using the two production functions $y_t = Z_t h_t^C$, $N_t^E = Z_t \cdot H_t^E / f^E$ and labour market clearing $H_t = N_t h_t^C + H_t^E$, leads to:

$$C_t = Z_t \rho_t \left(H_t - \frac{f^E N_t^E}{Z_t} \right) \tag{1.31}$$

so for a given aggregate labour supply H_t, new product entries soak up resources and crowds out the consumption goods sector.

The output of the consumption goods and variety producing sectors is defined as $Y_t \equiv C_t + v_t N_t^E$, where the latter term is investment (into new varieties).

I focus on the financial shock in the form of asset writeoffs, wr_t, that follows the process $\ln wr_t = \rho_{wr} \ln wr_{t-1} + \varepsilon_t^{wr}$. I assume productivity and the capital adequacy constraint remains constant. This leaves room for interesting analyses in optimal macroprudential policy in the form of countercyclical capital ratios, but I leave this for future research.

1.3.8 Calibration

For the vast majority of the real sector, the calibration follows BGM. In the baseline calibration, periods are treated as quarters. Thus, β is set to 0.99 to match 4% annualised average interest rate. Product destruction rate is set to $\delta = 0.025$ to match the annual product destruction in Bernard et al. (2010). I set the disutility of labour parameter ξ to ensure a steady state total hours worked of 1. Steady state productivity Z and entry cost f^E are also set to 1. These are merely normalisations with no impact on the impulse responses. Frisch elasticity φ is set to 4, following BGM. The habit formation parameter b is set to a conventional value 0.75, like in Gertler et al. (2012). The steady-state elasticity of substitution θ is calibrated to 3.8, from Bernard et al. (2003) to fit US plant and trade data.

The Dotsey-King parameters η and γ are calibrated to match the steady state markup implied by the steady-state elasticity of substitution and the markup elasticities. This markup elasticity is calibrated to the results of industry-level regressions on Table A.1 in the Appendix. The data is annual from 1990-2006 at six-digit NAICS level. It is then merged with the number of establishments from the BLS QCEW database. This results in a panel database of 479 industries. The markup elasticity chosen is -0.56 for the model with competition effects, and the counterfactual with almost no competition effects has an elasticity of -0.02. As previously mentioned, a markup elasticity of zero is achieveable if $\eta = 0$ where the Dotsey-King aggregator collapses to a Dixit-Stiglitz CES aggregator. However, due to the discontinuities in the preferences, I elect to use a very low markup elasticity instead. This is to see the impact of competition effects are, rather than a comparison of preference structures.

It is also important to note that these elasticities are significantly higher than those suggested by translog preferences, of around -0.18 (Lewis and Stevens, 2012), compared to the baseline estimate of -0.56 that is used in the quantitative analysis. This demonstrates the importance of using a more flexible preference structure with the Kimball aggregator as described earlier.

The banking sector parameters are calibrated to match the impulse responses and steady-state averages. The CAR is set to 0.1489, to match average observed equity to loan ratio of banks in aggregated Federal Reserve Call Reports data. In addition, I use the average spread of C&I loan interest rates over the Federal Funds Rate of 0.49% per quarter. With this, the steady state writeoffs wr is calibrated to ensure the model's steady state loan to deposit rate spread matches the data.

The loan adjustment cost and the AR(1) coefficient of the writeoff shocks determine the persistence of the loan contraction. The AR(1) coefficient is set to match an AR(1) regression of the Loan Officers' survey on credit standards, implying $\rho_{wr} = 0.89$. The loan adjustment cost is calibrated in order to match persistence of the VAR loan contraction, from the peak effect, that lasts for 10 quarters – resulting in $\kappa = 20$. In turn, the standard deviation of the writeoff shock is set so that the peak loan contraction matches the peak impact of the credit shock on the VAR impulse response in C&I loans, at 5.76%.

1.4 Simulation Results

In this section, I simulate a one standard deviation writeoff shock, calibrated to the VAR IRF as previously mentioned. This is equivalent to 1.23 % of assets.

As noted in Ghironi and Melitz (2005) and BGM, empirically relevant variables – rather than welfare-consistent variables – net out the effect in the product variety available. In short, consumer price indices do not adjust the basket for the availability of new products at business cycle frequencies, unlike the welfare-consistent price index P_t. Therefore, CPI is closer to p_t, as opposed to P_t. Thus, to compare to data, the data-relevant variables (i.e. deflated by a data-consistent price index), $X_{R,t} = P_t X_t / p_t = X_t / \rho_t$ should be used to compare to the data instead. However, the welfare-consistent variables remain important – they are what drives the dynamics of the model.

The impulse responses plotted of real variables – that is, those deflated by the welfare-consistent price index P_t – are the data-consistent version. The impulse responses for the welfare-consistent versions are in the appendix. Product investment is defined as the value of new variety creation, $v_t N_t^E$.

On the impulse responses in Figure 1.3 and 1.4, I plot two lines. The solid blue line is the baseline case of (near-) constant markups. The dashed red line is the empirically estimated markup elasticity of -0.56. Therefore, one compare the difference between the impulse responses as the effects of competition. This financial shock induces the bank to reduce loan issuance to satisfy the capital adequacy ratio. Given that the parent firm is dependent on bank loans to finance its investment into new varieties, product investment immediately falls and somewhat persistently so due to the bank's loan adjustment costs. Consumption also falls on impact because less income being generated from the upstream suppliers. On impact, there is no effect on the number of varieties N_t, given that it is a pre-determined variable.

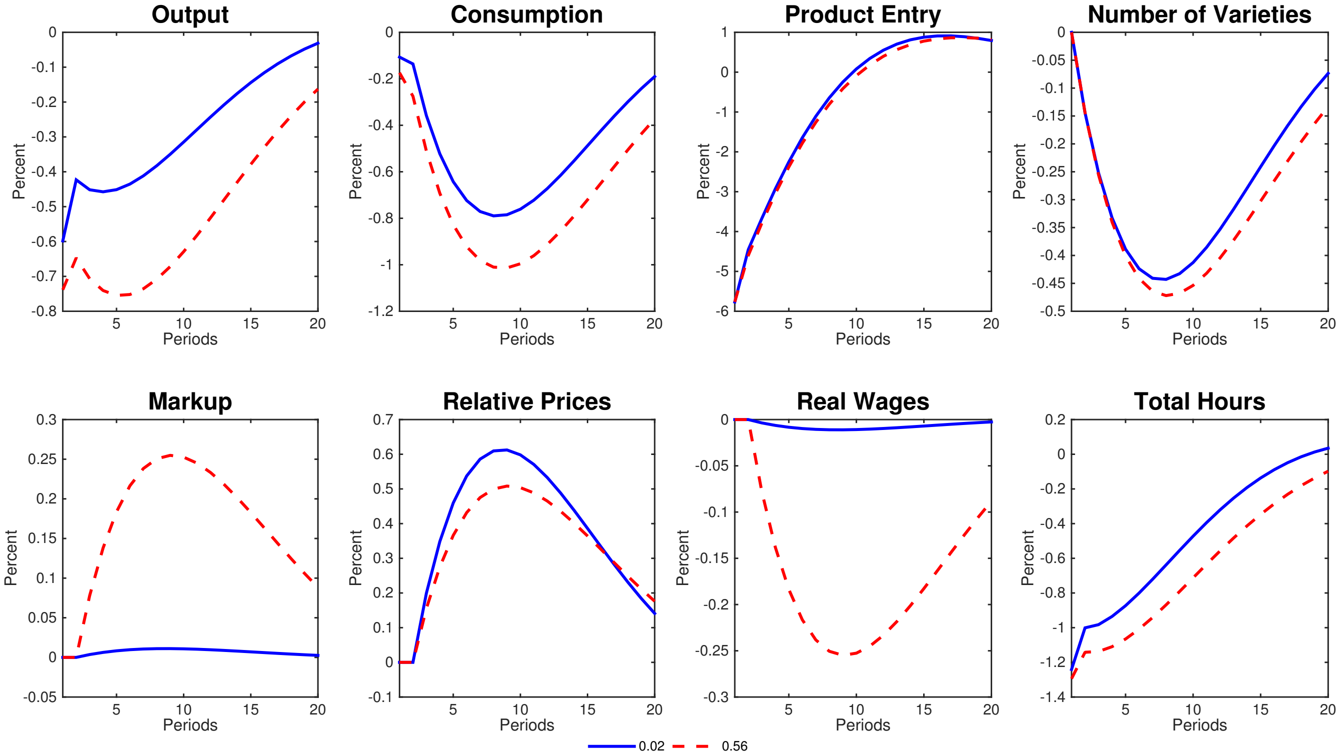

Figure 1.3. Impulse Responses of Real Variables to a Credit Contraction

Note: The credit contraction is modelled as a one standard deviation shock to equity capital writeoffs. The solid blue line shows the response of the (near-)constant markup model, and the dashed red line is the variable markups model (with a markup elasticity of -0.56).

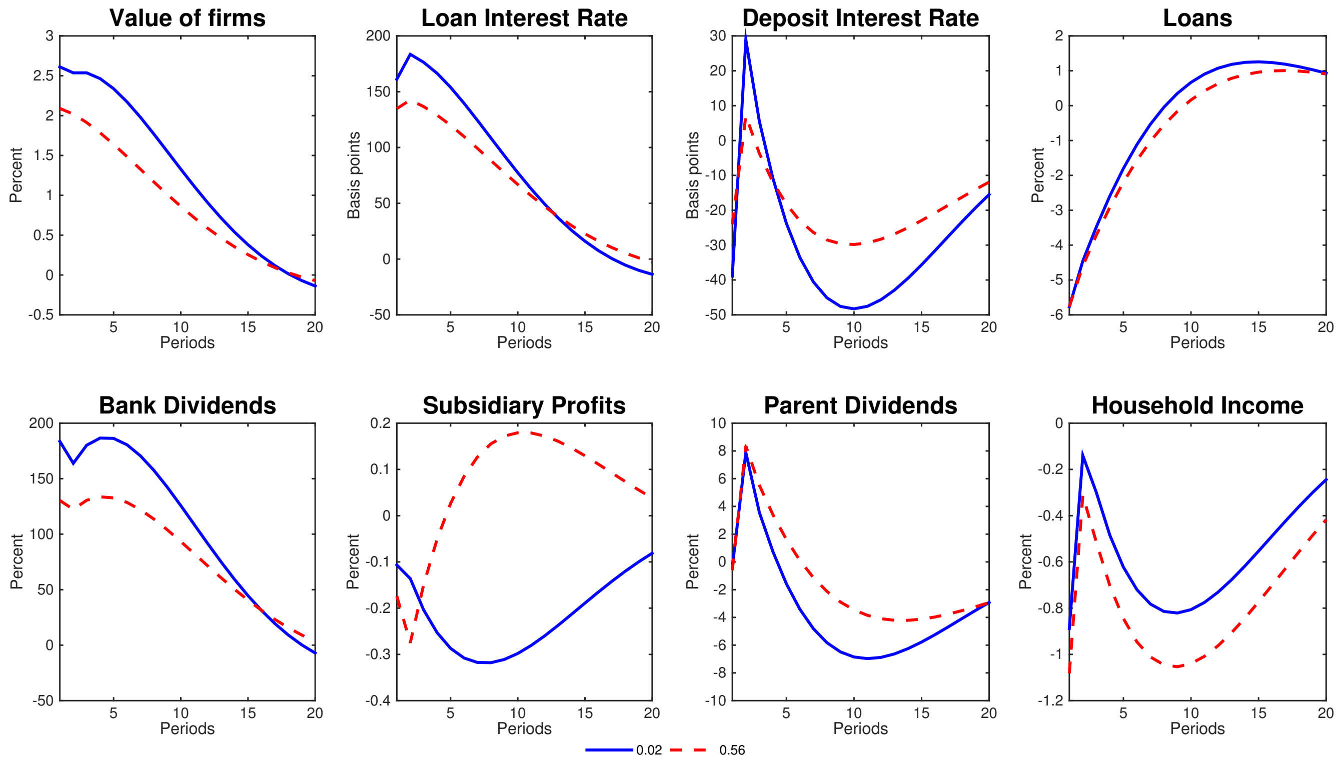

Figure 1.4. Impulse Responses of Financial Variables to a Credit Contraction

Note: The credit contraction is modelled as a one standard deviation shock to equity capital writeoffs. The solid blue line shows the response of the (near-)constant markup model, and the dashed red line is the variable markups model (with a markup elasticity of -0.56).

Then, the impulse responses begin to diverge, in particular for consumption. A markup elasticity of -0.56 implies the peak impact of the financial shock on consumption is 28% larger than the case of constant markups. On average, this amplification results in consumption is 19% more volatile when there is variable markups. The mechanism works from to two interlinked channels – competition and the labour market. Firstly, over time as the number of varieties begin to fall, markups also start to rise for the model with competition effects. This results in markups increasing, decreasing demand as prices are higher than other they would have been under the constant markup case.

Secondly, the competition channel's amplification effects in enhanced by the labour market. In particular, the decrease in demand in the product market leads to the same decrease in labour demand. This induces real wages fall more under variable markups, relative to the constant markup model.[7] With GHH preferences, this results in a fall in hours worked due to the substitution effect, reducing the output of the consumption good producing sector. Combined, the drop in real wage and hours worked lead to an even larger decrease in household income, which contributes to the fall in aggregate demand. As Figure 1.4 shows, the reduction in household income closely mimics the fall in consumption. Jermann and Quadrini (2012) also emphasise the role of hours worked for financial shocks to have real effects. They use a working capital constraint that forces firms to borrow to pay their wage bill in advance. This mechanism ensures that financial

[7]Note that these are the data-consistent variables. The welfare-consistent real wage actually rise (see Appendix), but in the model with variable markups, they do not rise by as much. The rise in the relative price imply that the data-consistent real wage hardly moves under constant markups.

shocks translate to movements in hours worked, and thus, aggregate fluctuations.

The behaviour of the value of a *new* variety v_t increases above the steady state is somewhat counterintuitive. This is caused by equation (1.24), where the value of a new variety is equalised to the cost of entry. As the cost of entry increases due to loan interest rates increasing, v_t also increases. Intuitively, this can be thought of that due to the scarcity of funding, only projects into new products with a high return are funded. This is consistent with survey evidence that suggests start-ups that begin operations during a recession are more likely to be profitable in the future.[8]

The fall in varieties is amplified mildly in the model with variable markups, which in turn amplifies the increase in markups, due to v_t being lower under variable markups. This occurs despite the increase in markups leading to an increase in profits at each subsidiary. The cause is due to the higher cost of equity by the parent firm, which governed by the household's stochastic discount factor. The steeper fall in consumption implies that households would prefer to have dividends now in order to smooth out their consumption, rather than the parent firm investing into new varieties to get long-term profits. This makes the parent firm discounts future profits by each subsidiary more, and discourages it to invest into new products, exacerbating the fall in varieties and the rise in markups.

The amplification is also mild because of a general equilibrium response from banks. The bank reacts to (relatively) lower loan demand by lowering interest rates – or at least, loan interest rates do not increase by

[8]Hiscox International DNA of an Entrepreneur Report 2014

as much.[9] In the impulse response for loan interest rate, the difference does not seem much (around 40 basis points). However, considering that the steady state loan interest rate is only 150 basis points per quarter, this represents a fairly significant boost to encouraging investment.

Note that the banking sector recovers its equity capital and loan-issuing capabilities after around 10 quarters after the shock, as a result of the calibration of the loan adjustment costs and persistence of the writeoff shocks. Meanwhile, consumption recovers after around 20 quarters with constant markups, and with variable markups, even longer than that due to high markups persisting after credit supply is restored. Furthermore, the balance sheet variables of the bank does differ slightly across the markup elasticities. From the reduced loan demand, lower loan interest rates imply reduced spreads. This results in the bank's equity capital base recovering more slowly. This occurs even when the banks are handing out less dividends to the households under variable markups.

Bank dividends actually increase after the financial shock, despite the fact that there is a scarcity of equity capital. This is because of the loan adjustment costs.[10] It is too costly to extend loan in the aftermath of the financial shock, reflective of the lack of investment opportunities and difficulty in monitoring that loan adjustment costs is supposed to capture. This is exactly what a firm should do when it has a lack of profitable investment opportunities – buybacks to the shareholders. However, it has

[9] Loan interest rates still increase from steady state because of a scarcity of bank equity capital.

[10] Without adjustment costs, the equity capital base recovers much more quickly. Dividends go negative (i.e. an equity issuance) which partly helps to boost the capital base, but not fully as it is very expensive to do so when the marginal utility of consumption is already high. Most of the capital recovery is through retained earnings, as spreads become very high.

the ramification that the equity capital base takes longer to recover. A policy implication would be to restrict dividends to ensure the recovery of the capital base, as many governments have done to systemically important banks in the aftermath of the 2008-10 financial crisis.

It is worthwhile repeating that investment – given that there is no physical capital – is defined as the value of new varieties, $v_t N_t^E$. In a model with physical capital, I expect the behaviour to be much more similar to consumption. The investment goods sector is also subject to decreased competition and increased markups during a credit crunch. Therefore, it would have the same effect of dampening investment good demand as the relative price of investment increases. The increase in new variety investment is likely to have minimal impact as new variety investment is a much smaller part of GDP, relative to physical capital investment.

1.5 Empirical Results

In this section, I compare the DSGE model's predicted impulse responses to the financial shock to the IRFs of a VAR, both qualitatively and quantitatively. Recall that the DSGE model is calibrated to match the persistence and size of the impulse response of loans and the credit standards index. The aim of this exercise is to see given this calibration strategy focusing on the financial sector, whether the DSGE model can match the empirical dynamics of the *real* sector. More specifically, I seek to test if the predicted mechanisms through competition and the labour market also exist in the data. In addition, I examine whether the consumption path predicted by the variable markups model fit the VAR's impulse response well. The grey

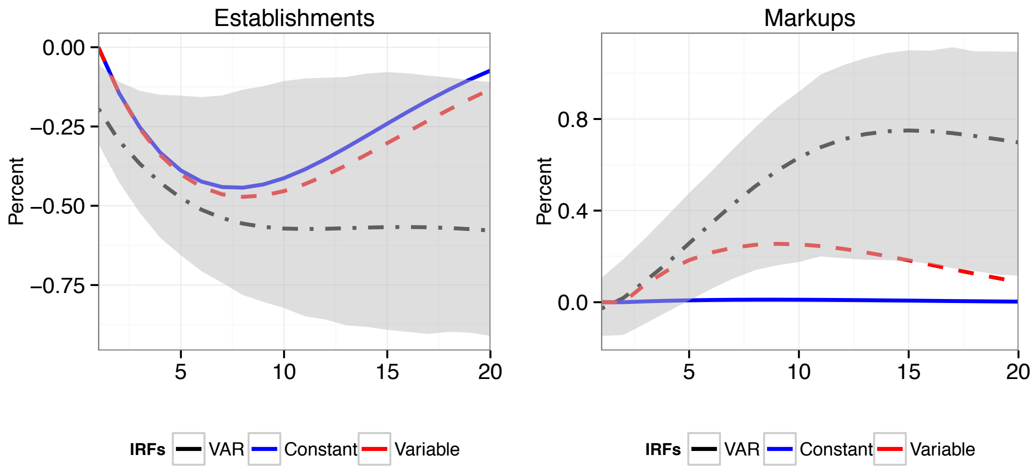

Figure 1.5. Competition variables

Note: The solid blue line is the theoretical impulse response for the (near-)constant markup DSGE model, and the dashed red line is for the variable markup model with an elasticity of -0.56. The dash-dot black line is the VAR's empirical impulse response in Section 1.2.2

bands are 90% bootstrapped confidence intervals.

As already demonstrated in Section 1.2.2, the VAR suggests the competition mechanism exists. The movements of the number of varieties, both the constant and variable markups models, exhibit similar dynamics. In Figure 1.5, it shows that both models get quite close quantitatively to the VAR's impulse response in N_t to a credit standard tightening shock – especially in closely matching the peak impact of the shock, and the horizon of the peak impact. With respect to markups, obviously the model with constant and variable markups vary in dynamics. The variable markup DSGE model's does seem to underestimate the peak effect. This could be because of other factors affecting the markup that the model does not capture (for example, nominal rigidities), or an under-estimation of the true markup elasticity. While I calibrate the elasticity to 0.56 to the micro-data evidence in the nexdt section, the VARs suggest that the markup elasticity

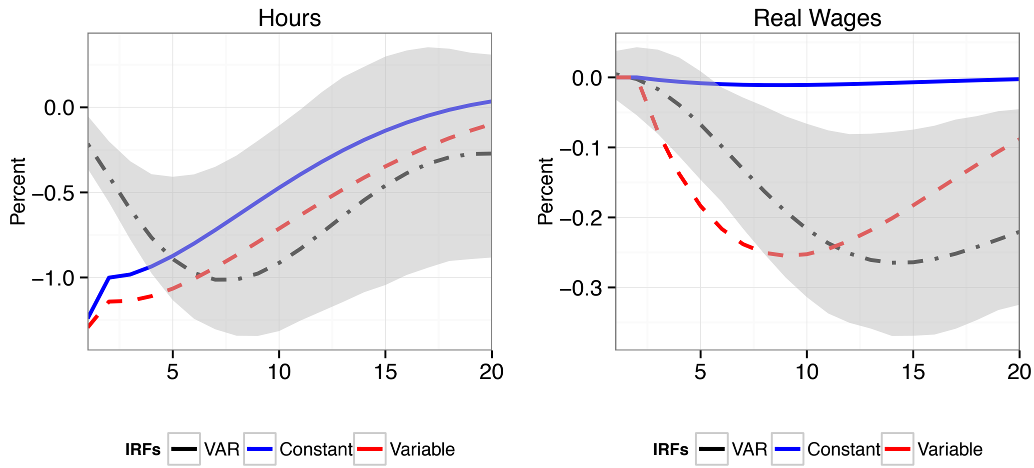

Figure 1.6. Labour market variables

Note: The solid blue line is the theoretical impulse response for the (near-)constant markup DSGE model, and the dashed red line is for the variable markup model with an elasticity of -0.56. The dash-dot black line is the VAR's empirical impulse response in Section 1.2.2

could be larger than 1 – establishments fall by 0.6%, while markups rise by almost 0.8%. Section A.2.1 explains that on calibrating this elasticity to the manufacturing micro-data will explain in greater detail that the DSGE model's calibration is a lower-bound estimate. Note that the Gilchrist et al. (2014) predicted markup dynamics (strong effect on impact after a credit supply shock) that is not supported by the data. A slower-moving markup that is driven by competition seems to fit the data better.

Secondly, in Figure 1.6, I examine the predicted mechanism through the labour market. For this, we need to add the relevant labour market variables to the VAR.[11] I use the Non-farm Business Sector Hours for hours worked, and Total Private Real Average Hourly Earnings of Production and Nonsupervisory Employees for real wages. The VAR is recursively identified as before, with the order: $\mathbf{X}_t = [cs_t \; N_t \; \mu_t \; w_t \; h_t \; y_t \; \pi_t \; r_t \; l_t]'$.

[11] All IRFs for this VAR can be seen in Figure (A.6) in the Appendix.

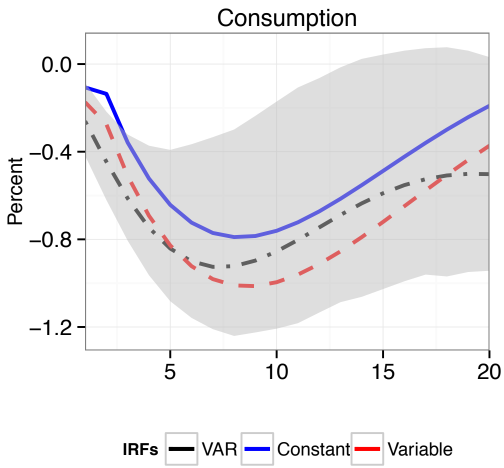

Figure 1.7. Consumption

Note: The solid blue line is the theoretical impulse response for the (near-)constant markup DSGE model, and the dashed red line is for the variable markup model with an elasticity of -0.56. The dash-dot black line is the VAR's empirical impulse response in Section 1.2.2

Given the large size of the VAR, information criteria suggest that one lag is optimal. In hours worked, the DSGE model's predictions does not vary much with constant or variable markups. They both get quite close to the peak effect on hours in the VAR, but fail to replicate the hump shape. A crucial mechanism and prediction of the DSGE model is through real wages, where there is a marked difference between constant and variable markups. The VAR evidence supports this predicted mechanism after the credit contraction shock. The DSGE model quite closely matches the trough of the IRF, although underestimating the horizon of it by five quarters. Like the IRFs of the markups, the constant markup model falls out of the confidence bands while the variable markups stay mostly within it (and somewhat closely to the point estimate).

Lastly, in Figure 1.7, I demonstrate the predicted consumption path of the DSGE model under variable markups closely track the VAR, until the trough. The constant markup case is out of the 90% confidence interval in the first few quarters. The peak impact of the variable markups case is also very close to the VAR's, while in the constant markup case underestimates the peak impact (albeit remaining inside the confidence bands). To summarise, this subsection documents how the DSGE model's prediction come close to the empirical VAR impulse responses through the two key mechanisms, and matching closely the path of consumption once competition effects are allowed to enter.

1.6 Conclusion

To conclude, by augmenting an endogenous product variety RBC model with financial shocks, I have described a novel transmission channel of financial shocks. Using the DSGE model, I demonstrate that competition effects can amplify the effect of a financial shock on consumption by 28% through an increase in markups, leading to a slow recovery of consumption after the financial shock. This is the core amplification mechanism. Empirically, using aggregate data, I show that the predicted competition effects occur after a bank credit supply contraction – competition falls and markups rise, as well as the effects through the labour market that depress household income. This brings the implication that if policymakers decide to use demand-side policies to stimulate the economy after a financial shock (as the appropriate response to a demand shock) – then they would need to be take into account the effects of higher markups on the natural level of output. The increase in market imperfections imply a decrease in the natural level of output. This is important in order for policymakers to not overestimate the amount of slack in the economy, which would lead to excessively stimulatory policies and high inflation. While the current model has already shown its success in matching the behaviour of consumption, future avenues of research is to add physical capital investment to enhance the model in two dimensions. One would be to reproduce the dynamics of output by taking into account physical capital investment and how the investment goods producing sector are also exposed to reduced competition and subject to the same amplification mechanism as consumption goods. Secondly, the mechanism would propagate the shock even further, as higher start up costs from more expensive capital goods would disincentivise entry, leading to a greater persistence of lower competition and high markups. In addition, the variable markups mechanism also leads to an explanation to why the estimated DSGE literature finds such large and highly persistent markup shocks, which are inconsistent with the micro data evidence on reset price inflation in Bils et al. (2012). An upcoming research project is to embed this mechanism in a Smets and Wouters (2007) type model and see how much of the variance in markups can be explained by other shocks, through the competition effect.

Chapter 2

Beyond Inventory Management: The Bullwhip Effect and the Great Moderation

2.1 Introduction

Despite the Great Recession, understanding the causes of the period of prolonged macroeconomic stability that preceded it (known as the Great Moderation) remain important. This is because if that period was driven mostly by good luck, as suggested in Stock and Watson (2003), Ahmed, Levin and Wilson (2004), Kim, Nelson and Piger (2004) and Herrera and Pesavento (2005), then there is no reason to expect such stability to resume. Studies that estimate the changes in the reaction function of the Federal Reserve like Clarida et al. (2000), Cogley and Sargent (2001), Orphanides (2004) and Boivin and Giannoni (2006) are proponents that better monetary policy was a main driver. Stability induced by better monetary policy is more likely to be continued.

New business practices, often taken to mean better inventory management techniques, is a third suggested cause for the Great Moderation and are also likely to be a more persistant driver of lower volatility. McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Kahn et al. (2002) suggested there was a substantial role for inventory management. However others, such as Stock and Watson (2003), consider the role for inventory management and dismiss it. McCarthy and Zakrajšek (2007) using a VAR analysis of the Great Moderation concluded that inventory management played, at most, a supporting role. The reason earlier papers tend to dismiss a role for new business practices is related to the focus on inventories and is summed up nicely by Taylor (2013):

> *"Firms cut inventories when sales weaken and rebuild inventories when sales strengthen. Better inventory control could thus explain the improved stability. But this explanation also had problems. When one looked at final sales – GDP less inventories – one saw the same amount of improvement in economic stability."*

Our main contribution in this paper is to extend the concept of business practices to include supply chain management and backordering behaviour in addition to inventory management. Importantly, we will argue that changes in business practices can endogenously dampen sales volatility. As such, the reduction in sales volatility is not sufficient to reject a central role for new business practices. Davis and Kahn (2008) considered the potential contribution of supply chain management in the Great Moderation, but leaves how it connects with sales volatility as an open question.

We focus on the durables manufacturing sector. We do this for a number of reasons. First, despite accounting for only about 20% of GDP, durables production is one of the biggest contributors to output volatility.[1] Second, it is also one of the biggest contributors to output moderation as a result of a large fall in within-sector volatility (Stock and Watson, 2003); a back-of-the-envelope calculation from the results in Stock and Watson (2003) suggests that it accounts for around half of the overall Great Moderation (see Table B.1 in the appendix). Third, McConnell and Perez-Quiros (2000) and Davis and Kahn (2008) show the timing of durables output volatility falls, impeccably matches the observed break in GDP volatility. Finally, manufacturing industries are placed upstream of the supply chain, and therefore, has the most to benefit from the new business practices; for example, backorder books are sizeable in durables manufacturing.

We make two specific empirical contributions. First, motivated by the finding of Zarnowitz (1962) that firms respond to demand shocks by accumulation/depletion of backorders first (changing lead times), we document how the Great Moderation was not just a period of lower inventory investment volatility but can also be characterised by quicker delivery, shorter lead times and reduced use of backordering in the durable goods manufacturing sector. To explore what these developments mean for the analysis of the effects of new business practices, rather than focus on the production identity that states production (Y) is equal to the sum of sales (S) and inventory investment (ΔI), we further disaggregate sales into its

[1] About 2-2.5 times more volatile than non-durables, and 6-10 times more than services (Table 7 in Stock and Watson (2003)).

components of new orders O and adjustments to backorders ΔU:

$$\begin{aligned} Y &= \quad S \quad &+\Delta I \\ &= (O - \Delta U) &+\Delta I. \end{aligned} \tag{2.1}$$

We find that reduced volatility of new orders accounts for the majority of sales and production volatility falls. Given that the previous literature claims that the decline in sales volatility is most likely driven by background macro factors (good luck or good policy), a similar argument would likely be adopted to explain declining new order volatility. They would consider this as similar evidence that we need to look at alternative explanations to new business practices. However, given that most orders in the manufacturing sector are placed by intermediate goods producers, rather than consumers, supply chain management can be an important determinant of order volatility. We argue that improved business practices can endogenously dampen order volatility; upstream suppliers meeting new orders consistently more quickly can give rise to a reduction in the volatility of sales. This is unlike the analysis in standard macroeconomic models of inventories.

The second empirical contribution is to show that improved business practices contributed substantially more to the Great Moderation than previously thought. While still not the dominant contributor, this channel can account for 20-25% of the output volatility declines. This finding comes from our application of the empirical approach of McCarthy and Zakrajšek (2007) (MZ hereafter) to our broader concept of business practices in the durables manufacturing sector. We estimate a separate structural

VAR for the pre-1979 (High Volatility, HV) and post-1984 (Low Volatility, LV) period. Using forecast standard errors as a measure of volatility, we ask the question if volatility reductions emanate from luck and macroeconomic changes, better business practices (identified as sector-level structural changes), or a combination of both.

Counterfactuals between the two SVARs suggest that sector-level structural changes have contributed to approximately half of the fall of new orders volatility. We interpret this as the result of a dampening of the *'bullwhip effect'* (Lee et al., 2004) – the well-documented phenomenon where demand shocks from downstream consumers are amplified through the supply chain to upstream producers. New business practices, such as the adoption of Electronic Data Interchange ICT systems, which led to better communication along supply chains, would diminish the amplification of new orders volatility and stabilise production.

We also find evidence of changes in backordering behaviour. The successful adoption of lean production and just-in-time techniques reduces the need for backorders to smooth out demand shocks and, as a consequence, delivery times would lower and more consistent. Finally, we find that implied inventory volatility (as a proportion of inventory stocks) in the durables sector actually increases.[2] This is suggestive of the adoption of flexible production processes, as predicted by most macroeconomic models of inventories and production flexibility such as Alessandria et al. (2013) and McMahon (2012).

The rest of the paper is organised as follows. Section 2.2 describes

[2]The MZ result that inventory volatility has fallen holds in the non-durables manufacturing SVAR (reported in the appendix). This indicates that particular result was driven by the much larger non-durables sector.

the data used and establishes some motivating stylised facts. Section 2.3 details the bullwhip effect that the empirical evidence we present in this paper supports. Section 2.4 introduces the structural vector autoregression, and the counterfactual methodology. Section 2.5 analyses the results and implications for the role of business practices on the Great Moderation. Section 2.6 concludes.

2.2 Inventories and Backorders: Technologies and Evolution

There can be no doubting that the business practices have evolved a great deal since the 1960s. This is particularly true in the context of new technologies that allow firms much greater control over their production, sales and distribution processes. In this section, we first review the types of technological improvements that many practitioners consider as driving forces for improved management of inventories and distribution.

We then examine developments in the durables manufacturing sector to see how inventories (disaggregated into stages of production – materials and supplies, work-in-process and finished goods inventories) and backordering evolved before and during the Great Moderation. We do this using industry-level monthly data from the United States Census Bureau. The historic time series for *Manufacturers' Shipments, Inventories & Orders* covers January 1967 to December 1996. All variables are in current dollars (by net selling values) and seasonally adjusted. To deflate the variables, we use the implicit sales price deflators from the Bureau of Economic Analysis.[3]

2.2.1 Backordering and the Bullwhip Effect

Before we turn to an analysis of the new technologies that have affected (in particular) the manufacturing sector, we describe two important related characteristics of manufacturing supply chains. Specifically, we examine the use of backordering and the bullwhip effect. We believe that these characteristics are key to understanding the Great Moderation but are generally under-researched areas of macroeconomics.

Zarnowitz (1962) documented that firms respond to demand shocks by accumulation/depletion of backorders first (changing lead times), then adjusting inventories, and eventually changing production and/or prices. The role of backorders is particularly relevant in durables manufacturing where backorder books are sizeable.

The bullwhip effect is well-documented in the management science literature. It is a supply-chain phenomenon whereby demand shocks from downstream consumers are amplified through the supply chain to upstream producers. This is caused by a systematic distortion of demand information through the supply chain, when the manufacturers only observe its immediate order data (and not further down the supply chain), and there are lead times and ordering lags. Lee et al. (2004) group the causes into four categories: demand signal processing, shortages and rationing gaming, order batching, and price variations. Let us look in more

[3]Deflating the nominal variables using these price deflators makes the implicit assumption that the intra-sector composition of inventory investment, backorders and new orders are the same as sales.

detail at how each of these causes gives rises to extra volatility in the manufacturing sector (and to make clear how some are directly related to the use of backordering).

Firstly, demand signal processing occurs by the need of producers to forecast future demand by using their immediate customer's orders. If there are lead-times in production and delivery of raw materials, positive autocorrelation of demand, and each member of the supply chain processes the order signals from below, shocks are amplified as it goes upwards through the supply chain.

Secondly, shortages are a period of more extensive use of backordering. This contributes to the bullwhip effect when customers attempt to manipulate their supplier's rationing. If the producer delivers a good that is short in supply, as a proportion to total orders, the customer will place extra 'phantom orders' in order to get the goods. When the supply shortage eventually clears, they cancel their phantom orders and thus, the producer sees amplified fluctuations in their order book.

Thirdly, order batching occurs when a firm's own demand comes in, depleting inventory, but they may not place an order immediately with its supplier. This may be due to the fact that material requirement planning (MRP) systems are run only monthly, or due to firms attempting to get economies of scale from delivery and order processing costs.

Finally, price variations may lead a customer to attempt to build inventory during times of low prices, and the opposite when prices are high. This leads to large, irregular orders. Such periods of low and high prices may follow from over-reactive production which means it is both a result of, and contributor to, the bullwhip phenomenon.

2.2.2 New Technologies Affecting Durables Manufacturing

Improvements of supply chain management are based on the introduction of ICT-based systems and lean production. To understand why these might have a profound effect on the production of durables, we now discuss some of the main developments and link them to our two important channels. We stress three broad developments (which are again related):

1. *Electronic Data Interchanges (EDIs)*
2. *Vendor Management Inventory (VMI)*
3. *Just-in-Time Production (JIT)*

The adoption of ICT systems by manufacturers, and all along the supply chain, allowed for widespread use of EDI. That is, computers from one firm in the supply chain could send information to another firm in a standardized format and with little need to human intervention. This has led to better communication, and vitally better information, along supply chains.

VMI shifted to the (upstream) manufacturer the responsibility for maintaining appropriate inventory levels at downstream links in the supply chain (such as a wholesaler). The downstream firm simply agrees to provide detailed and timely information on sales and inventory levels. The manufacturer can then optimally allocate resources across each of the (potentially many) downstream firms.

JIT or lean manufacturing is an approach to manufacturing which originated in Japan and is associated with Toyota. It made its way to the West in 1977. It involves reduced waste and lead times in production which in turn facilitates greater flexibility in the manufacturing. A simplistic view of flexible manufacturing is that it leads to more volatile production. However, flexibility to meet demands in a more responsive fashion (for example, by changing production focused on one product to another) may actually give rise to greater stability. Moreover, as we will argue, reduced and more consistent lead times by the manufacturer may endogenously change ordering behaviour by downstream firms.

It should be clear that these three new business practices are interrelated. For example, while VMI was an impetus for widespread adoption of EDI (in exchange for information the downstream firm no longer had to manage the inventory), it is also the case that VMI could only work because of EDI. Causality similarly runs both ways when we consider JIT and EDI or JIT and VMI; VMI/EDI led to faster delivery response times, and computerised flow production which allowed firms to more easily adjust production.

2.2.3 The Evolution of Durables Manufacturing: Some Stylized Facts

Regardless of the extent to which these new practices caused each other, it should be clear that they – at least potentially – could give rise to profound effects on the use of backordering and the bullwhip effect. In this subsection, we establish some stylised facts on the evolution of the durables manufacturing sector over time and particularly in the Great Moderation. These facts can shed light on the the aforementioned channels through which better practices can lead to lower order volatility, by demonstrating the effects of the adoption of improved supply chain management techniques and flexible production processes. These stylised facts can be grouped into the following:

1. *Reductions in production materials lead times*

2. *Reductions in lead time volatility*

3. *Reductions in backorders-sales ratios*

4. *Reductions in inventories-sales ratios*

Since firms respond faster by adjusting production, delivery times became lower and more consistent. Figure 2.1 shows that there have been large falls in production materials delivery lead times. There was also a sharp reduction in lead times from pre-1980s, and post-mid-1980s (mean of 72 and 49 days, respectively). This is shown in figure 2.2. These declines began in the early-1980s and coincide with a rapid increase in firms achieving JIT ordering; Figure 2.2 shows that the proportion of manufacturing firms with JIT ordering (defined as receiving orders in less than five days) more than tripled from before the 1980s to the Great Moderation period.

As we will argue below, it is not only the first moment that affects ordering behaviour, but also the variance of lead times. This relates to the reduction in the backorder adjustment margin and increased consistency of delivery times. As a proxy for leadtime disruptions, we calculate rolling volatilities of the Institute for Supply Management's Manufacturing Supplier Deliveries Index[4]. We use this index, rather than raw delivery

[4]The volatilities are calculated by the Q_n estimator of scale.

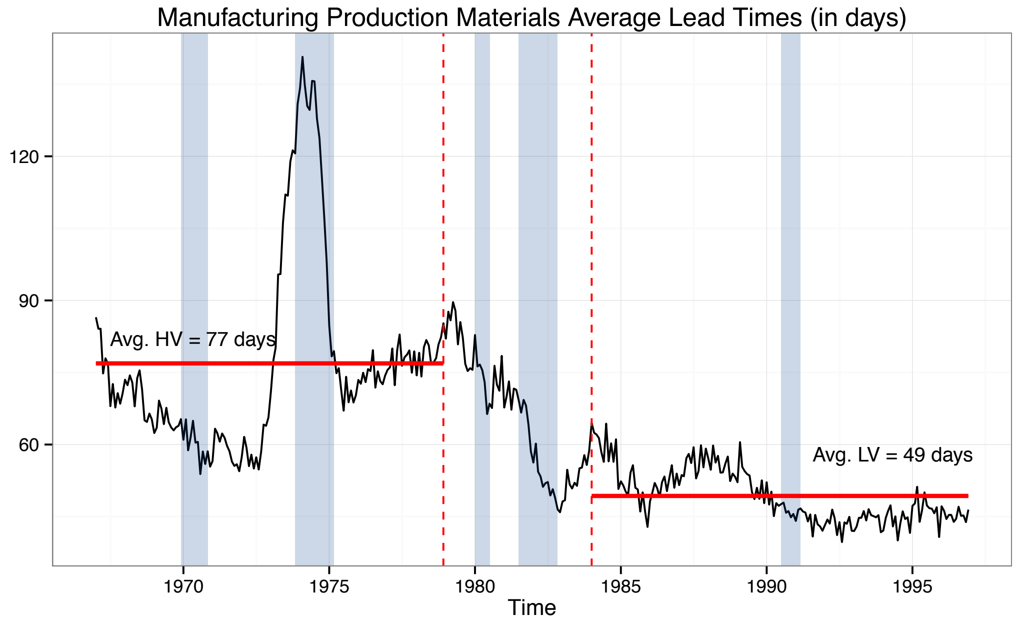

Figure 2.1. Average Manufacturing Production Materials Lead Times

Note: Institute for Supply Management data. Shaded areas are NBER-dated recessions.

times, as it is calculated like the Purchasing Managers' Index – it emphasises *changes* to delivery times, which is the crucial factor in determining disruptions to production scheduling. In Figure 2.3 this shows a sharp decline in volatility from the early 1980s. Increased delivery consistency allows manufacturers to improve production scheduling, and implement just-in-time practices to respond to demand shocks faster.

JIT allows producers to respond faster to demand fluctuations and so allows firms to reduce backorder books. There is also less need to use backordering because, through VMI, the manufacturer can essentially reduce desired inventory while they adjust production smoothly. We see there is a large fall in durables sector backorders (relative to sales) in the early 1980s (figure 2.4).[5] However, this decline occurred only gradually

[5] We exclude the Transportation sector due to its special characteristic of extremely

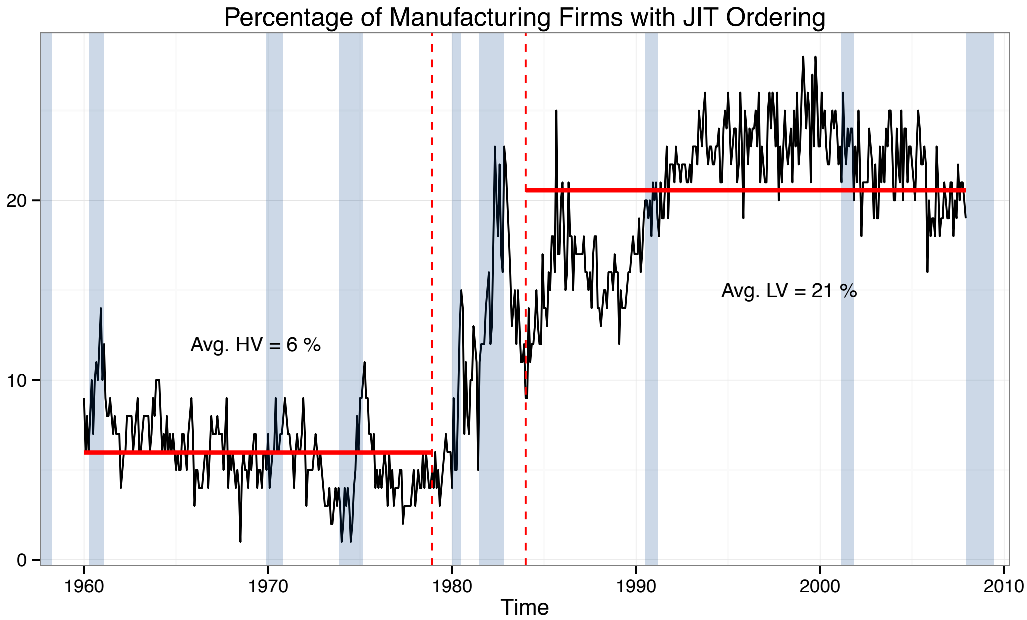

Figure 2.2. Percentage of Manufacturing Firms with Just-in-Time ordering

Note: JIT defined as receiving orders in less than five days. Shaded areas are NBER-dated recessions.

and is not as stark as the previous stylized facts. This might be expected given it is a stock variable and so may take somewhat longer to adjust. It is worth noting that while the backorder-book size has declined, the higher frequency volatility remains relatively high. This is important as it is the change in backorder books, and not the size of them, that affects production volatility.

Finally we turn to the evolution of inventories – the focus of most of the previous literature. Inventories-sales ratios for the durables sector have also fallen since the early 1980s (Figure 2.5). This was driven mostly by materials and supplies inventories first in the late 1970s (and to a lesser

long lead times, which would not be informative on the state of supply chain management. The total durables manufacturing and disaggregated data is available in the appendices.

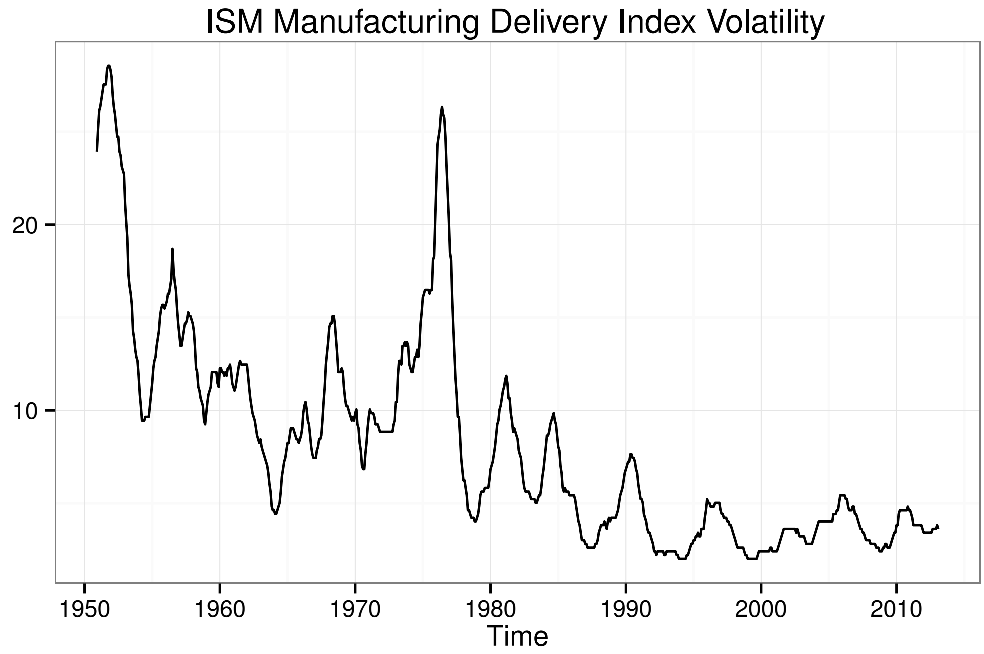

Figure 2.3. Volatility of ISM Manufacturing Deliveries Index.

Note: Authors' own calculations. Calculated as the 36-month Backward-Looking rolling standard deviation of the ISM Manufacturing Deliveries Index.

extent, final goods inventories). It was only in the 1990s that holdings of work-in-progress inventories fell strongly. This suggests steady improvements in inventory control but perhaps not as starkly occurring at the time associated with the start of the Great Moderation.

2.3 Analysis of Volatility: Role of New Business Practices

The previous section presents evidence of the effects of new business practices in durables manufacturing. Importantly given the existing literature,

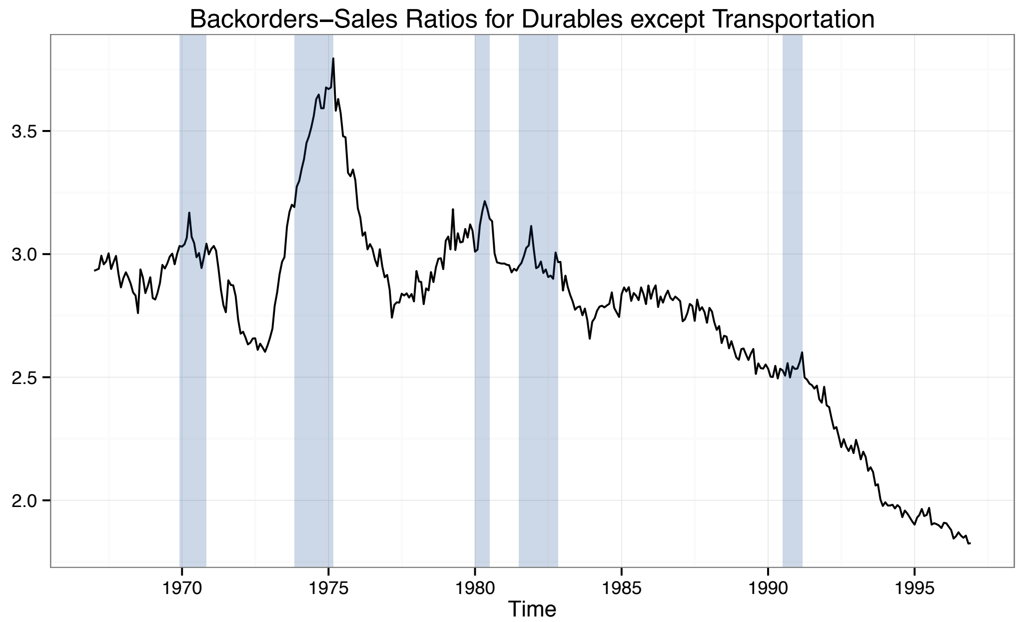

Figure 2.4. Backorders to Shipments Ratio (excluding Transportation sector)

Note: We exclude the Transportation sector due to its special characteristic of extremely long lead times, which would not be informative on the state of supply chain management. Shaded areas are NBER-dated recessions.

the evidence pointed to effects outside of simply changes in how inventories are managed. We also suggest that these changes should affect volatility. We therefore now turn our attention to the behaviour of volatility in the durables manufacturing industry.

We will focus on the comparison of two twelve-year periods to try to capture the 'steady state' volatility in each period. The first period covers January 1967 to December 1978 and we call it the High Volatility (*HV*) period (as MZ do). The second is the Low Volatility (*LV*) period covering January 1984 to December 1996.[6] This split follows MZ and allows for a transition period from 1979 to 1983 during which the exceptional volatil-

[6]We stop in December 1996 to ensure comparable data across the *HV* and *LV* periods.

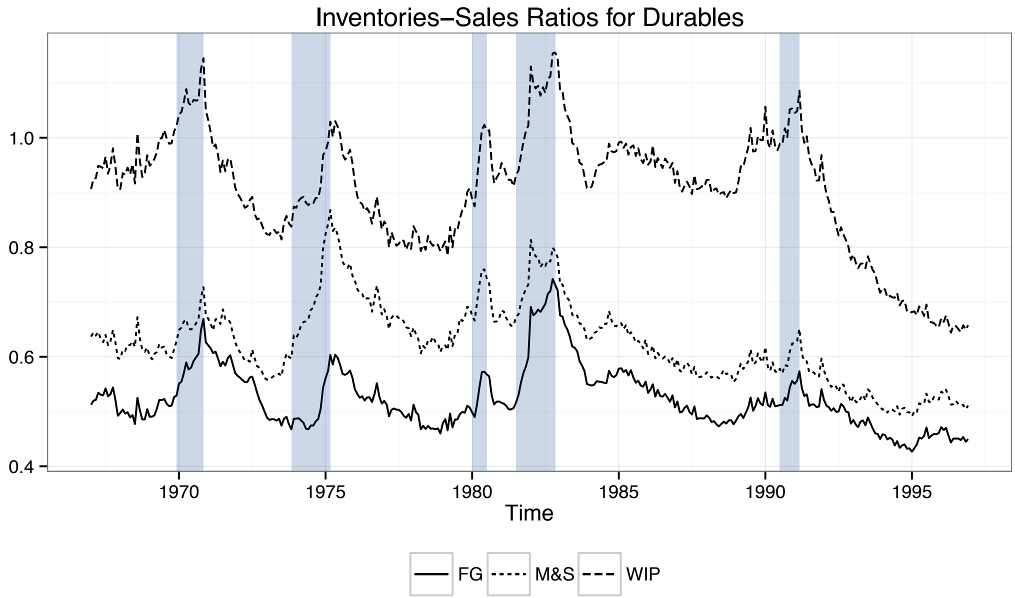

Figure 2.5. Inventories to Shipments Ratio

Note: We exclude the Transportation sector due to its special characteristic of extremely long lead times, which would not be informative on the state of supply chain management. Shaded areas are NBER-dated recessions.

ity of the Volcker disinflation and extensive manufacturing restructuring may contaminate the results. (Some of the figures we presented of inventories and backorder behaviour clearly show that this interval was indeed a transition period.)

2.3.1 Volatility Decomposition

In this subsection we document a volatility decomposition of durable manufacturing production volatility. We use (2.1) applied to quarterly growth rates (meaning that the RHS terms are quarterly growth contributions) and then examine the following volatility decomposition (where $V(x)$ denotes the variance of x and $cov(x,z)$ denotes the covariance of x and z):

$$V(Y) = [V(O) + V(\Delta U) - 2cov(O,\Delta U)] + V(\Delta I) + 2cov(S,\Delta I). \quad (2.2)$$

In Table 2.1 we present this decomposition in the form of standard deviations for the HV and LV periods. The advantage of using standard deviations is that it allows us to express everything in terms of five core driving parameters:

1. $\sigma_{\Delta I} \equiv \sqrt{V(\Delta I)}$ is the standard deviation of the change in inventories
2. $\sigma_O \equiv \sqrt{V(O)}$ is the standard deviation of new orders
3. $\sigma_{\Delta U} \equiv \sqrt{V(\Delta U)}$ is the standard deviation of the change in backorders
4. $\rho_{S,\Delta I}$ is the correlation coefficient between S and ΔI
5. $\rho_{O,\Delta U}$ is the correlation coefficient between O and ΔU

The other terms of equation (2.2) can be expressed as functions of these five parameters. For example, $cov(O,\Delta U) = \rho_{O,\Delta U}(\sigma_O)(\sigma_{\Delta U})$ and $V(S) = \sigma_O^2 + \sigma_{\Delta U}^2 - 2\rho_{O,\Delta U}(\sigma_O)(\sigma_{\Delta U})$. Of course, we have to be careful as variances – not standard deviations – are additive. Therefore, we also present the relative change in variances too.

This decomposition reveals that the three core variance terms all declined between the periods. In particular, the variance of new order quarterly growth contributions fell by 51% after 1984. The variance of inventory investment fell 4%. The correlation between sales and inventory investment increased, but by a very small amount in absolute terms. The correlation between new orders and backordering was broadly stable. The

		HV	LV	$\frac{\sigma_{LV}^2-\sigma_{HV}^2}{\sigma_{HV}^2}$	$\frac{\sigma_{LV}-\sigma_{HV}}{\sigma_{HV}}$
Core Parameters	$\sigma_{\Delta I}$	1.1	1.0	-4%	-2%
	σ_O	5.6	3.9	-51%	-30%
	$\sigma_{\Delta U}$	3.6	3.1	-28%	-14%
	$\rho_{S,\Delta I}$	0.04	0.12		
	$\rho_{O,\Delta U}$	0.77	0.79		
Resulting Volatility	σ_Y	3.8	2.7	-50%	-29%
	σ_S	3.6	2.4	-57%	-33%

Table 2.1. Volatility decomposition of durable manufacturing production

Note: Quarterly growth contributions in percentage points. High volatility period (HV) covers 1967:1-1978:12; Low volatility (LV) period covers 1984:1-1996:12. The third column is the percentage change in the variance (which are additive) between HV and LV periods. The fourth column is the percentage change in the standard deviation. Identity used is $Y = S + \Delta I = (O - \Delta U) + \Delta I$.

variance of changes in backorder books declined by 14%. Taken together, the changes in give rise to a 57% fall in sales variance and a 50% decline in production variance. This corresponds to a 33% and 29% fall in the standard deviations, respectively.

Unlike the findings in McConnell and Perez-Quiros (2000) for the aggregate economy, there is little evidence that changes in inventory investment volatility, nor the cyclicality (correlation) of inventory investment, contribute to the stabilisation of durable manufacturing. Almost all stability arises from the fall in sales volatility and particularly new order volatility declines.

To be more precise, we perform a counterfactual exercise asking how much would production volatility have declined if *only* $\sigma_{\Delta I}$ fell to its LV level (with other parameters remaining at HV levels). Using the decompo-

	Realised	Counterfactual changing: σ_O only	$\sigma_{\Delta I}$ only	$\sigma_{\Delta U}$ only	*corr* only
σ_Y^2	-50%	-47%	0%	7%	-1%
		(94%)	(1%)	(-15%)	(3%)
σ_S^2	-57%	-52%	-	8%	-6%
		(91%)	(-)	(-14%)	(11%)

Table 2.2. Counterfactuals for changes in variance between *HV* and *LV* periods

Note: The first column is the realised change. The next three columns document what would be the change in production or sales variance, if *only* the variance of the particular variable was changed to the *LV* period. The last column is the same exercise, but changing the correlations only instead. The numbers in parentheses is the proportion of the realised decline in variance that the counterfactual explains.

sition in Table 2.1, this is an easy exercise:

$$V(Y)^{Alt} = (\sigma_O^{HV})^2 + (\sigma_{\Delta U}^{HV})^2 - 2\rho_{O,\Delta U}^{HV}(\sigma_O^{HV})(\sigma_{\Delta U}^{HV}) + (\boldsymbol{\sigma_{\Delta I}^{LV}})^2 + 2\rho_{S,\Delta I}^{HV}(\sigma_S^{HV})(\boldsymbol{\sigma_{\Delta I}^{LV}}) \tag{2.3}$$

In Table 2.2, we repeat the exercise changing the appropriate parameters to ascertain what would have happened to production (and sales) volatility if only σ_O or $\sigma_{\Delta U}$ changed.

If only the inventory investment term, changed production volatility would have declined a very small amount (variance falls by a tiny 0.3%). On the other hand, by changing new orders volatility, the implied production variance falls by 47% – which makes up 94% of the actual decline we observe. In contrast, changing backorders volatility actually increases production variance slightly. This is because the fall in backorder variance does not compensate enough for the less-negative covariance term. In addition, as expected given the small changes in correlations, changing only the correlation components (both $\rho_{O,\Delta U}$ and $\rho_{S,\Delta I}$) has very little impact on production and sales volatility.

2.3.2 The Role of New Technologies in Order Volatility

Although only an illustrative decomposition, this analysis essentially produces the same result that led earlier studies to conclude that changes in inventory management practices did not drive the volatility reduction associated with the Great Moderation. We agree with the previous literature that to explain the fall in production volatility, one has to explain the moderation of sales volatility. In fact, we push this finding further and show that it is really new orders volatility that needs to be explained. However, we do not conclude that this analysis rules out a role for new business practices.

Given the types of new business practices we have discussed, we need to think more carefully about where would expect changes in the decomposition table. For example, while we saw that backorder books have declined in size, it is the volatility of quarterly growth contribution that matters most for the decomposition exercise. The effects of less backordering may actually show up as reduced volatility of new orders; with less backordering, there is less use of phantom orders which reduces volatility in orders and would mute the bullwhip effect.

In a similar vein, by allowing upstream producers access to downstream demand data, EDI should alleviate demand signal processing difficulties and contribute to less amplification of volatility up the supply chain. The better information means that manufacturers are less likely to be surprised by changes in orders, or can better identify purely transitory movements in downstream demand. JIT allows producers to respond faster to demand fluctuations and therefore intermediate goods producers know they will receive extra orders speedily if they themselves experience a demand shock. In response to shorter and more consistent delivery times, intermediate goods producers stop making large, irregular orders when lead times are low (previously necessary to build up materials inventories and avoid costly materials stockouts).

We believe that new business practices can endogenously change the volatility of orders; other researchers have interpreted orders or sales as exogenous processes (to new business practices). Our interpretation leaves open a clearer role for new business practices, and in particular the dimensions of supply chain management discussed above.

Such endogenous demand processes are not standard in typical models of business cycles and inventories. For example in the RBC model of Alessandria et al. (2013), retailers buy an input subject to both idiosyncratic demand uncertainty and re-order uncertainty. A new business practice that reduces the inventory-sales ratio 15% (a figure from Khan and Thomas (2007)) would increase output volatility slightly. Similarly, in McMahon (2012), more flexible distribution technology leads to greater (not lesser) volatility of production for given other exogenous processes.

However, in the operations research literature such endogeneity is more common. In fact, in that literature the dependence of new order volatility on backordering behaviour and lead times variability is well-established. For example, Song and Zipkin (1996) shows that consistent lead times on a firms own orders affects inventory and ordering behaviour. Song et al. (2010) show that in response to stochastically shorter lead times, customers will optimally reduce the amount of safety inventory that they hold and reduce the size of orders. The response to less-variable lead times is, however, ambiguous.

Of course, the overall effect of new business practices is an empirical question. Our decomposition, while interesting, does not allow us to conclude that there was or was not a crucial role for new business practices. However, it does convince us that any role should manifest itself through reduced new orders volatility onto increased stability of durable goods production. Of course, nothing precludes the macroeconomic factors from driving these changes; reduced downstream aggregate demand volatility as a result of good luck or good policy could also lead to lower upstream order volatility. We have merely argued that new business practices may be an adequate explanation.

We now want to push our analysis further, and especially to establish more clearly the direction of causality. To disentangle between the three effects and establish causality, we now adopt a multivariate approach. This VAR analysis will allow us, subject to our identification scheme, to formalise the links between aggregate and the sector-level variables.

2.4 Separating Out Business Practices and Macro Effects

This section explores new order, inventory and backorder dynamics in the durables manufacturing sector, within a structural VAR framework. Building on the methodology of MZ, we examine possible structural changes in the economy by estimating separate SVAR models for the pre-1979 (*High Volatility*) period and the post-1984 (*Low Volatility*) period. We then apply a counterfactuals decomposition methodology that follows Stock and Watson (2003) as well as Simon (2001), to analyse the structural contribution of each variable to overall forecast error variance. In this section we will make clear the specific approach we use and the identification assumptions we make.

2.4.1 The SVAR Model

The defining feature of the MZ approach is the separation between the *aggregate* and *industrial* block of variables. The reduced-form VAR is as follows:

$$\begin{bmatrix} \mathbf{x}_t \\ \mathbf{y}_t \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11}(L) & \mathbf{A}_{12}(L) \\ \mathbf{0} & \mathbf{A}_{22}(L) \end{bmatrix} \cdot \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{y}_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_t \\ \mathbf{u}_t \end{bmatrix} \tag{2.4}$$

where $\mathbf{x}_t$ and $\mathbf{y}_t$ denotes the industry and aggregate block, respectively. The submatrix of zeros in the lower left shows the block exogeneity assumption.

This approach is similar the pseudo-panel VAR methodology of Barth and Ramey (2002) and Davis and Haltiwanger (2001). The coefficients within the aggregate block are constant for each industry that the VAR is estimated for; obviously each industry block has its own set of coefficients as well as industry-specific coefficients transmitting aggregate activity to the industry block. The main motivation of this pseudo-panel VAR approach is to achieve 'more efficient estimation' (a nine-variable VAR has many coefficients to estimate) and 'consistent identification of the monetary policy shock' (Barth and Ramey, 2002). The approach essentially relies on the dynamics of aggregate variables being well explained within the aggregate block (as is the case in standard VARs with aggregate only variables, for example, Bernanke and Gertler (1995)).

This means that, when we do the decomposition exercise, we can use changes in the aggregate block's parameters to capture macro level changes across the two periods. We will also examine whether there have been changes in the transmission of aggregate demand shocks (captured by a monetary policy shock identified in the spirit of Bernanke and Gertler (1995)) to industry-level variables.

Unlike the pseudo-panel VAR approach, in this paper we focus on the effects on only one industry – durables manufacturing (for reasons already discussed). The methodology can easily be extended to other sectors. We present the results for the non-durables manufacturing sector in the appendix.[7]

Relative to MZ, we follow our earlier analysis and include extra variables in our industry block: $\mathbf{x}_t = [o_t \; u_t \; \overline{p}_t \; m_t \; h_t]'$. New orders are denoted o_t and u_t is backorders. The relative price level, $\overline{p}_t$, is defined as the deviation of the log implicit sales price deflator from the log aggregate price level ($p_{it} - p_t$). Input inventories are m_t (materials and supplies, M&S). For the sake of parsimony, h_t captures the sum of final goods and work-in-progress inventories as they are both production outputs (incomplete and complete).

The aggregate block $\mathbf{y}_t = [e_t \;\; p_t \;\; p_t^c \;\; r_t]'$ consists of the aggregate economic activity measure e_t (we use private non-farm payroll employment

[7]Non-durables manufacturing had a smaller role in the overall Great Moderation, so it was not analysed in detail here. Nevertheless, the main results are broadly similar to durables.

since GDP is not available monthly), aggregate price level (PCE deflator) p_t, industrial commodities price index (commodities PPI) p_t^c and the Federal Funds rate r_t.

We transform each series apart from the Federal Funds Rate r_t by taking the logarithm and removing a stochastic trend using a one-sided exponential smoother filter.[8] There are two distinct advantages to using the one-sided exponential smoother filter. Firstly, since it is one-sided, there would be no end-of-sample issues as would be found with more common two-sided filters. Secondly, as Watson (1986) pointed out, since the filter uses past data to determine trends, this may mitigate issues associated with correlation between the filtered data and the residuals leading to inconsistent estimates.

The sample is separated into the two periods as we used for the volatility decomposition in Section 2.3: *HV* (1967:1 to 1978:12) and *LV* periods (1984:1 to 1996:12). As previously mentioned, the sample choice allows for a transition interval between the *HV* and *LV* periods. During this transition interval, average lead times falling dramatically (Figure 2.1) and the percentage of firms ordering just-in-time tripled, while it was fairly steady both before and after the transition (Figure 2.2). This approach enhances the ability to detect the effect of changes in business practices as well as monetary policy regimes.[9]

[8]As in Gourieroux and Monfort (1997), the smoothed series from the ES filter is $\hat{x}_t = gx_t + (1-g)\hat{x}_{t-1}$ where x_t is the actual data. Following MZ, the gain parameter g is set to 0.2. The main results were checked to be robust to $g = 0.1$ and $g = 0.3$.

[9]The transition could be endogenised by adopting a Markov-switching framework, but there would likely be very little value-added since it is already well-known that 1984 is the crucial period.

2.4.2 Identification of the SVAR model

The impulse responses and variance decomposition require an identification of the structural VAR. The intuitive restrictions on the contemporaneous relationships between the reduced-form VAR innovations imposed largely follows MZ, with some modifications to take into account of the split of sales into new orders and backorders. The vector of structural shocks are defined as:

$$\mathbf{A}_0 \cdot \begin{bmatrix} \mathbf{e}_t \\ \mathbf{u}_t \end{bmatrix} = \mathbf{B} \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \boldsymbol{\nu}_t \end{bmatrix}; \quad \begin{bmatrix} \boldsymbol{\varepsilon}_t \\ \boldsymbol{\nu}_t \end{bmatrix} \sim \text{MVN}(\mathbf{0}, \mathbf{I}_9) \tag{2.5}$$

where $\mathbf{B} = diag(\sigma_o, \ldots, \sigma_r)$ is a diagonal matrix of the standard deviations of the structural innovations. The contemporaneous relationships matrix $\mathbf{A}_0$ is:

$$\mathbf{A}_0 = \begin{array}{c} \\ o_t \\ u_t \\ \overline{p}_t \\ m_t \\ h_t \\ e_t \\ p_t \\ p_t^c \\ r_t \end{array} \begin{array}{c} \begin{array}{ccccc|cccc} o_t & u_t & \overline{p}_t & m_t & h_t & e_t & p_t & p_t^c & r_t \end{array} \\ \left[\begin{array}{ccccc|cccc} 1 & a_{12} & a_{13} & 0 & 0 & a_{16} & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 & a_{25} & a_{26} & 0 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 & 0 & a_{36} & a_{37} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} & 0 & 0 & a_{48} & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & a_{56} & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{76} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{86} & a_{87} & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & a_{96} & a_{97} & a_{98} & 1 \end{array}\right] \end{array} \tag{2.6}$$

The zero restrictions on the lower left part of the matrix reflect the block exogeneity assumption. The lower right part of the matrix exhibit the recursive ordering between the aggregate variables as in Bernanke and Gertler (1995). The ordering is such that the Fed Funds Rate responds to all aggregate variables contemporaneously (like a Taylor rule), and employment does not respond to any aggregate variable contemporaneously.

The upper left quadrant portrays the contemporaneous interaction between the industrial variables. As MZ describe it, the restrictions 'reflect the stickiness of price and production plans that are reasonable given the monthly frequency'. We adopt a similar identification scheme like MZ, where there is a recursive ordering similar to the aggregate block, with a few additions in the upper triangular. In particular, new orders o_t and backorders u_t may affect all industrial variables (a_{21} to a_{51}, and a_{12} to a_{52}). Relative prices $\bar{p}_t$ can influence new orders (a_{13}), as well as inventory stages (a_{43} and a_{53}). M&S inventories m_t can affect FG + WIP inventories h_t, while FG + WIP inventories can influence M&S inventories as well as backorders.

Inventories at the high frequencies are often used as adjustment margins, hence a flexible relationship with the sector-level variables is allowed. However, at this frequency, it is unlikely that relative prices would be affected contemporaneously by anything other than new orders and backorders. Similarly, it is doubtful that backorders are affected by other than new orders, or FG inventories (which is a substitute for backorders). Relative prices has an effect on backorders only through new orders (which is allowed), and M&S inventories are purely an input to production. Finally, new orders are only affected by backorders (indicator of lead times) and relative prices (the price adjustment margin) as the orders within a given month should only reflect the activity of the downstream producers, but also react to lead times of the durables manufacturers.

The upper right of the matrix shows how the aggregate variables are connected to the industrial block contemporaneously. We follow MZ again, but with shipments split up into new orders and backorders. Aggregate economic activity e_t can influence all variables, except M&S inventories (parameters a_{16} to a_{56}). This is the crucial variable that transmits demand into the sector. It is unlikely to affect M&S inventories as it is an input to production which is likely to be sticky within one month. The aggregate price level p_t can affect the relative price level (a_{37}) and commodity prices p_t^c can alter the M&S inventories (a_{48}). The aggregate price level is a component of the relative price level, thus allowing a contemporaneous relationship is sensible. The commodity price index proxies the acquisition cost of M&S inventories, hence permitting contemporaneous correlation for the pair. The zeros in this quadrant is reflective of the simple intuition that the aggregate block drives the demand for durables (ie. new orders) only through economic activity, while the variables within the aggregate block can affect each other through the recursive ordering.

The lag order for this monthly VAR is chosen by AIC (Ivanov and Kilian, 2005). Searching on a grid of asymmetric lags on the industry-level and aggregate variables results in two lags each for the *HV* period, and an asymmetric two and three lags for industry and aggregate blocks, respectively, in the *LV* period. Thus, we estimate the SVARs with the latter's asymmetric lag structure (2 lags on industry, 3 on the aggregate block). MZ has more asymmetry in the lags (four on industry, and seven on the aggregate). The reason that the lags suggested by AIC is smaller could be due to the large increase of the parameters to be estimated from adding one variable, into a nine-variable VAR. Using other (harsher) criteria such as Hannan-Quinn or Schwarz-Bayes results in a much shorter lag structure, which would be unlikely to capture the true data-generating process given the monthly frequency. Nevertheless, the main results are robust to a variety of other lag structures.[10]

2.4.3 Counterfactuals Methodology

The counterfactuals method as in Stock and Watson (2003) can disentangle if industry-level structure (affected by new business practices), or macro effects, produces the fall in volatilities. For this exercise we will measure the decline in volatility using the forecast root mean squared errors (RMSE).[11]

Better business practices

$$\begin{bmatrix} \mathbf{x}_t \\ \mathbf{y}_t \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11}(L) & \mathbf{A}_{12}(L) \\ \mathbf{0} & \mathbf{A}_{22}(L) \end{bmatrix} \cdot \begin{bmatrix} \mathbf{x}_{t-1} \\ \mathbf{y}_{t-1} \end{bmatrix} + \mathbf{A}_0^{-1}\mathbf{B} \begin{bmatrix} \varepsilon_t \\ \nu_t \end{bmatrix}$$

Better policy (macro) Good luck (macro)

Figure 2.6. Effects of the hypotheses on the SVAR (structural version of Equation 2.4)

Figure 2.6 shows schematically how the three hypotheses parse into changes in the SVAR. We will measure the *business practices* effect in each period $j \in \{HV, LV\}$ using the upper two quadrants of the lagged coef-

[10]The results were checked to be robust under symmetric VARs with 2, 3, 4 and 6 lags.

[11]Following MZ, the horizon used is 60 months ahead. This is long enough such that the forecast error variances approach the unconditional volatility of the variable, which is what we are interested in. The results are robust to longer horizons (90 and 120 months).

ficients $\{\mathbf{A}_{11,j}(L), \mathbf{A}_{12,j}(L)\}$, and upper two quadrants of the contemporaneous matrix $\mathbf{A}_{0,j}$). The upper right quadrant contains the bullwhip effect – the transmission and amplification of downstream demand to upstream orders. The upper left quadrant encompasses the flexible production and effects of reduced delivery times. We denote all the industry level parameters that capture the business practices effects as $\mathbf{\Gamma}_j$.

The *macro* effects are composed of the aggregate level parameters ($\mathbf{A}_{22,j}(L)$ and the lower right quadrant of $\mathbf{A}_{0,j}$), as well as the shocks. The lower right quadrant parameters incorporate how monetary policy has changed. For the main results, we are agnostic of the composition of the macro effects between good luck and good policy, as we are mainly interested in the amount of volatility reduction that can be allocated to new business practices as opposed to one of the macro hypotheses. We will collect all the coefficients associated with the macro effects in $\mathbf{\Lambda}_j$.

We use our estimated SVAR for two different counterfactual exercises. First, we perform a counterfactual analysis. Our two sets of estimated SVAR coefficients (one for each period) yield two sets of business practices effects, $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$, and two sets of macro effects (policy and shocks), $[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{LV}]$.The LV combination gives lower volatility compared to the HV for most variables. With particular attention on new orders, we mix between the business practices and macro factors to see whether practices, or general macroeconomic developments in monetary policy and shocks, produce the lower volatility.

The second analysis is a more traditional counterfactual between structure and shocks. This involves grouping the parameters $(\mathbf{A}_j, \mathbf{A}_j(L))$ into $\mathbf{\Theta}_j$, to denote the industry and macroeconomic structure at period

j and the structural shocks are grouped into $\mathbf{\Sigma}_j = \mathbf{B}_j'\mathbf{B}_j$. We can then perform the counterfactual exercises of what happens if, for example, only the shocks changed and the structures did not.

Additionally, we examine more standard forecast error variance decomposition (FEVD) and impulse response analysis. Specifically, to narrow down the mechanisms that drive the results of the counterfactuals, we examine the impulse responses (defined as log-point deviation) of the sector-level variables (Figure 2.7), as well as aggregate variables (Figure 2.8) to a 100 bps Federal Funds Rate increase.[12]

2.5 Results

2.5.1 Evidence of a role for new business practices

This subsection examines to what extent there is evidence of the new business practices that we have discussed. We explore the existence of the channels posited through which better business practices can reduce new orders volatility as well as other supportive evidence in the behaviour of other variables. This section uses all the analytical tools we just described.

The counterfactual RMSEs, shown relative to the HV period $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$, are shown in Table 2.3. As described before, we mix the coefficients that change to highlight which gave rise to the greater decrease in volatility. For example, if the combination of $[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{HV}]$ (LV period business practices, and HV macro structure and shocks) produces similar volatility reductions as the overall LV SVAR system, then we conclude that business practices

[12]IRFs to a 1% commodities price increase can be found in the appendices (Figures B.3).

	Relative RMSE		
	$[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{HV}]$ Practices	$[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{LV}]$ Macro	$[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{LV}]$ Total
New Orders o_t	0.72	0.79	0.59
Backorders u_t	0.83	1.14	0.70
Relative price $\overline{p}_t$	1.34	0.54	0.78
M&S Inventory m_t	1.77	1.07	1.21
FG Inventory h_t	1.33	2.10	1.21

Table 2.3. 60-month RMSE counterfactuals of business practices and macro effects

Note: RMSEs are relative to the *HV* micro and macro parameters/shocks, ie. $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$.

has been driving the volatility moderation. Similarly, macro factors would be attributed as the cause of the moderation if $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{LV}]$ is able to reduce enough volatility. If there are complementarities between parameters and shocks, then the volatility reduction would not be additive (although they usually get close to).

For new orders volatility, the counterfactuals indicate that new business practices contributed $1 - 0.72 = 28\%$ and macro factors $1 - 0.79 = 21\%$ out of the total reduction in volatility of $1 - 0.59 = 41\%$. Therefore, both practices and macro factors account for the stabilisation, contributing around half each.[13]

Further evidence is shown in the FEVD (absolute numbers for RMSEs) of industry-level variables found in Table 2.4. The FEVD suggests that more of new orders volatility is now explained by industry (rather than aggregate) variables. Table 2.5 shows that the 'sensitivity' of new orders relative to employment shocks have been reduced by 27%. This is consistent with a dampening of the bullwhip effect – the transmission between downstream demand to upstream orders.

[13] Note that the counterfactuals do not necessarily add up, but here they get close to doing so: $0.72 \times 0.79 = 0.57 \approx 0.59$.

One may worry that the macro factors somehow influence the transmission of aggregate variables to the sector-level variables (the top right quadrant of parameters). To address this, we can perform another counterfactual of changing the upper-left quadrant of parameters only (Table B.2 in appendices) – or in other words, changing specifically the sector-level interactions between the sector variables. This leaves out a part of the bullwhip effect (the transmission between aggregate demand to new orders), and emphasises the flexible production and just-in-time techniques. This alone achieves a $1 - 0.82 = 18\%$ reduction in new orders volatility, demonstrating the strong influence of the within-sector structure on new orders volatility.

There is also evidence of backordering behaviour change. In the *HV* period, the IRFs support the Zarnowitz idea of shipments and production smoothing using the backorder margin. For a contractionary demand shock (a 100 bps increase in the Fed Funds Rate), backorders are being run down until new orders start to recover. This is consistent with large variations in delivery times. However, in the *LV* period, backorder levels remain largely stable. In other words, delivery times become more consistent. More lean production enables faster reaction times to order disturbances, and customers are more certain they would receive goods faster and on time. This leads to the dampening of new order volatility.

The evidence of changes in inventory behaviour is, as the earlier analysis suggested, more complicated. The behaviour of M&S inventories and FG + WIP inventories are very similar. With the negative demand shock, all types of inventory stocks rise in the short term more in the LV period, before falling to suit the lower level of orders. However, the inter-

	Forecast Variance Decomposition (%)					
	RMSE	Own	o_t	u_t	Other Industry	Aggregate
High Volatility						
New Orders o_t	1.6		0.4	1.5	4.0	94.1
Backorders u_t	1.3		0.4	18.0	5.9	75.7
Relative price $\overline{p}_t$	0.5	6.1	0.1	0.2	0.0	93.6
M&S Inventory m_t	0.6	3.0	0.2	14.2	5.9	76.7
FG Inventory h_t	0.7	12.2	0.2	0.4	10.0	77.1
Low Volatility						
New Orders o_t	0.9		1.2	1.8	11.8	85.3
Backorders u_t	0.9		0.1	4.6	8.6	86.8
Relative price $\overline{p}_t$	0.4	34.1	0.2	0.7	0.3	64.7
M&S Inventory m_t	0.7	6.6	0.1	0.8	20.0	72.4
FG Inventory h_t	0.8	2.0	0.1	0.0	8.1	89.8

Table 2.4. 60-month Forecast Error Variance Decomposition

Note: The second column is the percentage of the forecast error variance that can be attributed to the the shock of the variable itself. The second , third and fourth columns is the FEVD to new orders and backorder shocks, and all other industry-level variables, respectively. The last column is the FEVD attributed to the macro block of variables.

pretation of this result is fundamentally different, as M&S inventories are inputs to the production stage, and FG + WIP are production outputs.

For M&S inventories, there could be two channels operating. Firstly, with better supply chain management, as well as reduced and consistent lead times, lead to more stable M&S inventory stocks as firms' suppliers can vary shipments faster as necessary. The second channel could be that flexible production leads to to manufacturers' consuming inputs with greater fluctuations, leading to more volatile inventories.[14] Given that M&S inventories are more volatile in the *LV* period, this suggests that the latter channel is dominant. The IRFs show that there is an accumulation of M&S inventories as new orders fall, suggesting that firms are cutting pro-

[14] A prediction of McMahon (2012) is when inventories become more flexible, they are more volatile.

	Industry					Aggregate			
	o_t	u_t	$\overline{p}_t$	m_t	h_t	e_t	p_t	p_t^C	r_t
New Ord. o_t	1.11	0.46	1.12	2.33	0.35	0.73	0.72	0.02	0.12
Backord. u_t	0.06	0.19	1.50	2.36	0.04	1.04	1.64	0.03	0.15
Rel. pr. $\overline{p}_t$	1.37	2.16	2.40	1.67	15.81	0.2	2.2	0.01	0.72
M&S Inv. m_t	1.26	0.09	39.4	1.18	0.09	5.62	1.58	0.11	3.33
FG Inv. h_t	0.53	0.23	1.07	2.88	0.41	7.84	1.65	0.11	0.75

Table 2.5. 60-month horizon relative sensitivity to structural shocks

Note: The sensitivity measures how the volatility of one variable (rows) is driven by a standardised shock of a particular variable (columns). See Simon (2001) for details on the calculation. The table reports the ratio of the sensitivity between the *LV* and *HV* periods: a ratio less than one indicates that the variable is less sensitive in the *LV* period.

duction faster (and symmetrically, are able to increase production quickly when there is a positive demand shock). Furthermore, despite the increase in structural shock variance, the counterfactuals indicate that overwhelmingly micro factors are responsible for the higher volatility (in contrast to FG + WIP inventories). This hints that flexible production techniques are operating in the *LV* period.

On the other hand, FG + WIP inventory dynamics play a role in stabilising production. However, the channel is somewhat different from MZ. The similarity is that we also find that FG + WIP inventories become more countercyclical with respect to new orders in the *LV* period. That is, inventories rise initially with the fall in new orders, before eventually declining when new orders start recovering. In contrast to MZ, all inventory type stocks become more volatile. The counterfactuals suggest that for FG + WIP inventories, this mostly comes from the macro factors (and from the conventional counterfactuals, aggregate structure) – hence this supports MZ's assertion that firms expect less persistent sales shocks, the perceived benefits of maintaining stable production increases. Combine the four facts that: the RMSEs (which approximates unconditional volatility) of inventories are much smaller than the RMSE for new orders; that inventories IRF rose by 0.2% while new orders fell by 0.5% in the *LV* period, in contrast to a negligible response of inventories with a 1% fall in new orders in the *HV* period; it is inventory investment that enters the production identity; and finally, inventory-sales ratios for durables hover around two. It is likely that the net effect of FG + WIP inventory dynamics to be more production smoothing.

As also found in MZ's IRFs, the *HV* period impulse responses behave almost cyclical (especially for new orders), although they decay back to zero after some periods. IRFs to sector-level variable shocks do not show this behaviour, thus this feature is driven from the aggregate block. In particular, the economic activity indicator exhibit the same wave as new orders, as well as aggregate and commodity prices with congruent timing of the troughs and peaks. However, could this be caused by fluctuating economic activity driving the swings in prices, or is the variability in prices inducing fluctuations in economic activity? The literature suggests a possible channel for the latter – the indeterminacy of the monetary policy rule in the *HV* period (the pre-Volcker era). For example, Lubik and Schorfheide (2004), Sims and Zha (2006) and others have documented that during the *HV* period the Federal Reserve did not increase nominal rates aggressively enough in response to a rise in inflation. This induces business-cycle fluctuations in output and inflation that would not occur if determinacy was satisfied. The IRFs to a commodity price shock (Figure B.3) is consistent with this story. A 1% increase in commodity prices induces a large increase in aggregate prices, and also large fluctuations in economic activity, in the

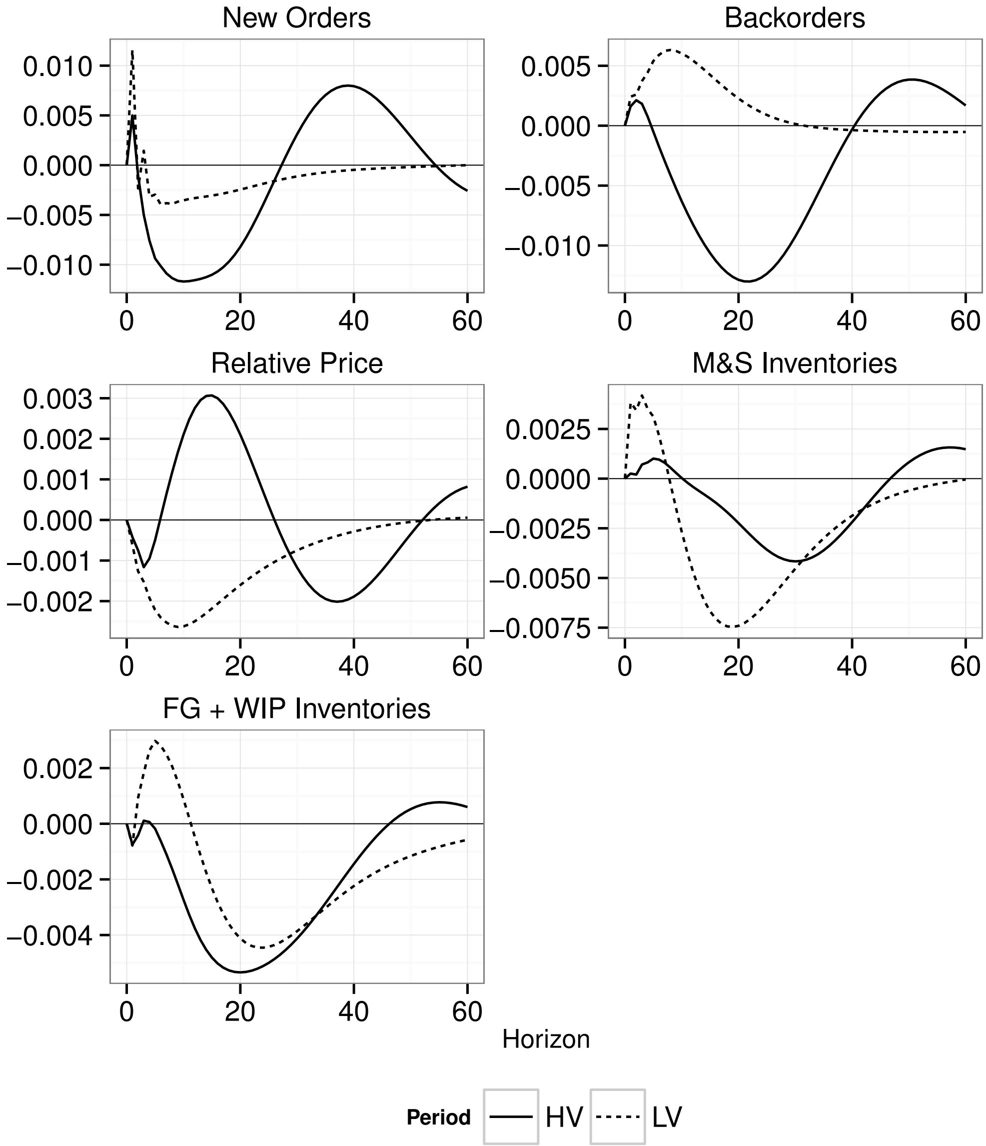

Figure 2.7. Durables impulse response to a 100 bps Fed Funds Rate increase

HV period. Meanwhile, in the *LV* period, a credible and aggressive Federal Reserve anchored inflation expectations such that the impact on aggregate prices and economic activity was negligible.

Taken overall, the main conclusion is that there is evidence for lean production and micro structural changes lead to more stable orders. Firms are more inclined to use FG inventories rather than backorders to stabilise production in the *LV* period. Greater flexibility in production processes and supply chain management leads to these dynamics, and in turn, this changes ordering behaviour such that it stabilises production. The results in Stock and Watson (2003) suggest that the durables good sector contributed to approximately half the overall output volatility moderation, despite its small relatively size.[15] Extending business practices to include supply chain management, our results suggest that business practices is responsible for approximately 40-50%. Combining the two, business practices have contributed to at least 20-25% of the overall Great Moderation. Better practices could have contributed more, through other sectors, or in other ways. Defining business practices as the changes in the sector-level parameters may or may not pick up the effects of better cash flow management, better hedging and others.

2.5.2 Evidence for macro effects

The previous subsection has highlighted that not only business practices contributed to the Great Moderation, but also the decline in aggregate demand volatility. We present evidence that supports both the narrative-

[15]See appendices for calculations.

Industry			Aggregate	
Shock to	Ratio		Shock to	Ratio
New Orders o_t	0.83		Employment e_t	0.62
Backorders u_t	0.80		Aggregate price p_t	1.01
Relative price $\overline{p}_t$	1.01		Commodities price p_t^c	0.75
M&S Inventory m_t	2.47		Fed Funds Rate r_t	0.97
FG Inventory h_t	0.60			

Table 2.6. Relative size of structural shocks, where Ratio = $\sigma(LV)/\sigma(HV)$

based literature (that the Great Moderation emanates from better monetary policy), as well as the VAR-based literature (that it was good luck).

The counterfactuals and IRFs suggest that the underlying macroeconomic background that feeds demand shocks into the industry-level variables has changed. The first point is that there is a large reduction in shocks. The structural variances of Table 2.6 indicates that the standard deviation of employment shocks fell by 38% in the *LV* period, and commodities price shocks by 25%. Like most VAR-based studies, this particular result is reconcilable with the good luck hypothesis.

However, it must be remarked that employment is an imperfect indicator of overall economic activity – greater labour market flexibility may induce greater employment volatility. The focus of the paper instead is on the components of sector-level durable goods production, which we know to be a large contributor of the Great Moderation.

On the other hand, unlike VAR-based evidence and similar to narrative-based evidence, we find significant aggregate structural changes. Firstly, the response of economic activity to monetary policy shocks in the *LV* period is much more muted. Secondly, the response of economic activity to a commodities price shock (Figure B.3) reveals how better monetary policy affects the economy differently. Commodity price shocks no longer cause

	Relative RMSE		
	$[\Theta_{HV}, \Sigma_{LV}]$ Shocks	$[\Theta_{LV}, \Sigma_{HV}]$ Structure	$[\Theta_{LV}, \Sigma_{LV}]$ Total
Industry			
New Orders o_t	0.78	0.73	0.59
Backorders u_t	0.77	0.84	0.7
Relative price $\overline{p}_t$	0.80	0.79	0.78
M&S Inventory m_t	0.86	1.54	1.21
FG Inventory h_t	0.82	1.69	1.21
Aggregate			
Employment e_t	0.80	1.24	0.92
Aggregate price p_t	0.96	0.91	0.88
Commodities price p_t^c	0.78	0.67	0.57
Fed Funds Rate r_t	0.84	1.80	1.33

Table 2.7. 60-month RMSE counterfactuals of structure and shocks

Note: The RMSEs are relative to the HV shocks and parameters, ie. $[\Theta_{HV}, \Sigma_{HV}]$.

economic activity fluctuations (or aggregate price level). This offers evidence that the macro structure has changed to stabilise exogenous shocks better. Noting the counterfactual (Table 2.7) that macroeconomic structure *increases* Federal Funds Rate volatility, this suggests that the Federal Reserve became more responsive to movements in output and inflation. This is consistent with past literature – for example, Clarida et al. (2000), Boivin and Giannoni (2002), Lubik and Schorfheide (2004) – that suggests the Federal Reserve's reaction function parameter to inflation have increased, and also Watson (1999) that the Federal Funds Rate became more persistent. Greater response and persistence induces more variability in the Federal Funds Rate. Thus, the isolation of the macroeconomic system from exogenous shocks appears to resulted from the Federal Reserve's credibility in fighting inflation.

This is also supported by the counterfactuals of commodity price

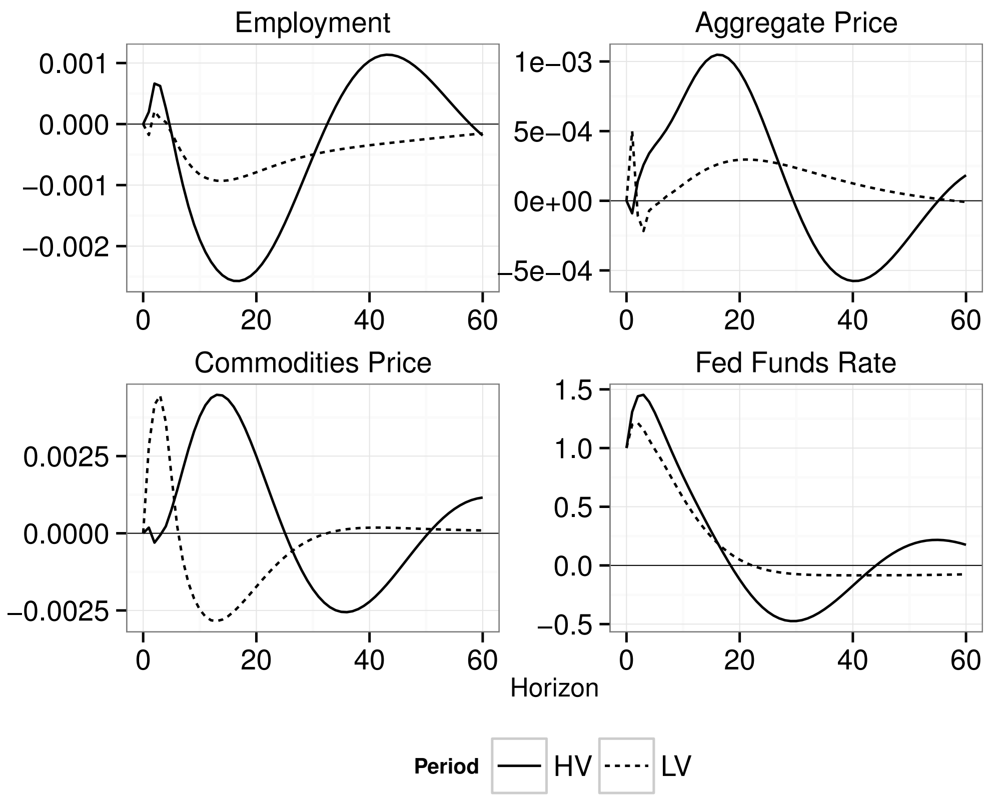

Figure 2.8. Aggregates impulse response to a 100 bps Fed Funds Rate increase

forecast errors. Shocks contribute to some reduction in volatility, but it is mostly from the sensitivity of the system (see Table 2.5). This explains why *LV* period impulse responses of all variables are much more muted, as well as returning to zero faster. Credible monetary policy anchored inflation expectations and price shocks do not become persistent. This is consistent with the results in McCarthy and Zakrajšek (2003) and Bernanke and Gertler (1995), where they found that aggregate output and prices responded less to oil price shocks post-1985.

Therefore, the results are consistent with the hypothesis that an aggressive Federal Reserve stance stabilised the macroeconomic system, deriving from reducing the impact of exogenous price shocks on real variables, rather than directly smoothing output.

2.6 Conclusion

In this paper, we revisit the important question of what gave rise to the Great Moderation. In particular, our main contribution is to extend the definition of new business practices to include aspects of supply chain management that fit much more closely with actual changes in practice than simply better inventory management practices.

Our empirical analysis supports a much greater role for new business practices in attenuating sales volatility in the durable manufacturing sector than most of the earlier literature. Our evidence is consistent with a reduction of the bullwhip effect and the effects of flexible production.

Most of the Great Moderation is still caused by the main macro factors – good luck and monetary policy. We present evidence that both play a role. Nevertheless, our results bring a case for optimism – around a quarter of the volatility reduction is due to better business practices (20-25%). Unlike the good luck result from most VAR-based studies, we can expect that this volatility will not easily return as the new technologies have changed supply chain management, and parts of our macroeconomic structures, forever.

Chapter 3

Leaning Against the Wind and Policy Tradeoffs

3.1 Introduction

"... monetary policy actions offer unfavorable and costly tradeoffs between macroeconomic and financial stability goals."

– John C. Williams (June, 2015)

A commonly observed mandate among operationally independent central banks is one that specifies a price stability objective, while avoiding substantial fluctuations in output. But in practice, central banks appear to occasionally adapt additional aims (Bernanke and Mishkin, 1992), and there has been much debate on the merits or otherwise of these extra goals. One particular focus of these discussions is whether monetary policy should be partially directed towards goals that contribute to financial stability, such as stabilising stock market booms.[1] However, as the quo-

[1] In cases where the mandate is sufficiently 'broad', and thus open to interpretation,

tation above makes clear, these additional objectives can entail tradeoffs. The aim of this paper is to describe and quantify the tradeoffs that monetary policymakers face if they decide to stabilise financial variables. We answer this question through the lens of an estimated dynamic stochastic general equilibrium model with financial frictions, and computing the set of feasible outcomes under policy commitment.

The debate has produced a range of perspectives. One view is that financial stability could be achieved by ensuring price stability.[2] The objectives were seen as complementary, and attainable by adopting a flexible inflation target (Bernanke and Gertler, 1999). This rested in part on a practical objection to directly targeting financial variables – that spotting asset price misalignments in real-time is difficult – and partly, on the observation that booming asset prices would anyway show up as higher spending and inflation, removing the need for a direct monetary policy response. Another view held that monetary policymakers should have regard for financial factors as such. This is often referred to as 'leaning against the wind' (hereafter, LATW; Bean, 2003).[3] While not rejecting the effect of asset price booms on demand and inflation, the proponents of LATW warned that 'mopping up' through looser policy after a sudden asset price reversal creates an asymmetry that could itself feed asset price booms (colloquially referred to as the 'Greenspan put').

In order to provide quantitative guidance on the choices available

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it makes sense to consider central banks as able to adopt policy goals–as having 'goal independence', in the terminology of Debelle and Fischer (1995).

[2]Microprudential regulatory tools, where they were under the control of the central banks, were seen as a sufficient bulwark against incipient problems in the banking system.

[3]In an earlier literature, leaning against the wind in monetary policy simply meant reacting systematically to the state of the economy, for example, according to a simple instrument rule (Taylor, 1999).

to policymakers who choose to LATW, we take a standard sticky-price macroeconomic model augmented with a banking system subject to financial frictions, estimate it on U.K. data, and simulate it under policy commitment. We are concerned with several related questions: How costly is it to reduce financial volatility in terms of output and inflation volatility? How does the output cost of reducing inflation volatility change as financial volatility is decreased? Which shocks generate the most significant tradeoffs? How do the answers depend upon the particular financial target chosen? Our main findings are that, first, LATW leads policymakers to face a strictly worse menu of inflation-output volatility choices, and that this deterioration is economically significant. Second, a greater degree of LATW makes inflation stabilisation increasingly costly in terms of output stabilisation. Third, LATW raises the marginal cost in terms of output and inflation volatility of reducing financial volatility. Finally, we show that – at least in the model studied here – placing a greater weight on inflation stabilisation can, on average, deliver levels of financial volatility that are similar to those achievable by a policy of LATW. Throughout, we show how LATW has effects that depend on the nature of the underlying disturbance, and on the precise variable that policy aims to stabilise.

The analysis of this paper focuses on how monetary policy can deal with financial imbalances, despite the substantial reforms of the regulatory framework of financial institutions (Committee on International Economic Policy and Reform, 2011). In particular, new macroprudential tools have been introduced in many jurisdictions, and in some instances placed under the authority of the central bank (Hanson et al., 2011). However, macroprudential tools remain – by and large – untested, and their effects highly uncertain. Furthermore, their scope is by nature limited to the regulated segment of the financial system, creating problems of policy 'leakages' between regulated and unregulated entities, and between domestic and foreign institutions (Aiyar et al., 2014; Pozsar et al., 2010). On the other hand, monetary policy is able to 'get in all the cracks', and have effects on the financial system beyond targeted regulatory tools (Stein, 2013). In this context, the LATW debate has taken on something of a new life.[4]

The reader should be aware of what we do not do in this paper. First, and most importantly, we do not provide normative prescriptions regarding the conduct of monetary policy under financial frictions. Although straightforward, that exercise would not address the question of how the tradeoffs between competing objectives change in response to central bankers paying greater heed to stabilising financial variables.[5] Second, our approach is firmly grounded in the extant literature on New Keynesian models with financial frictions, and we make no serious attempt to extensively modify the quantitative models used in the analysis. Consequently, our analysis shares the limitations of that model class, notably the absence of endogenous financial instability. Third, this paper does not consider how the introduction of a macroprudential policy instrument might improve the tradeoffs faced by monetary policymakers.

[4]Although framed squarely in terms of a second-best policy option, Svensson (2011, p. 1294–5) concedes that were financial policy unavailable, then 'to the extent that policy rates do have an impact on financial stability, that impact should be taken into consideration when choosing the policy-rate path to best stabilise inflation and resource utilisation.'

[5]In their normative analysis, Carlstrom et al. (2010) find that the weight on financial factors in the social welfare function is exceedingly small. As a result, they also analyse (much as we do) the consequences of arbitrarily up-weighting the significance of financial factors in the central bank's objective.

Related Literature

Even though our paper does not study the design of monetary policy, it is closely related to the literature that studies this issue in New Keynesian models with financial frictions. This is most importantly because our paper is motivated by some of this literature's findings that central banks should have regard for financial factors when setting monetary policy.[6] Moreover, since we construct efficient policy frontiers to address our question of interest, we follow the approach taken by several papers in this literature that monetary policy is conducted by policymakers who minimise a (quadratic) loss function subject to the (linearised) constraints of the decentralised economy, and where monetary policy is conducted under full commitment. But in contrast to the papers that use the linear-quadratic approach to study monetary policy design, we do not assume that policymakers minimise a loss function which is an approximation to the social welfare function.

Two approaches have been used to study whether the presence of financial frictions should alter the conduct of monetary policy. First, several papers analyse optimal simple monetary rules to understand whether in economies subject to financial frictions policymakers should respond in a systematic way to financial factors when their aim is to either maximise social welfare or to minimise an *ad hoc* loss function which reflects the central bank's mandate. Cúrdia and Woodford (2010) find that while a Taylor rule augmented with variations in credit spreads can improve upon the standard Taylor rule, a response to the quantity of credit is less likely to

[6]Smets (2014) provides an overview of the debate in the literature on whether or not monetary policy frameworks should take into account financial stability objectives.

be helpful. Gambacorta and Signoretti (2014) find that a Taylor rule augmented with asset prices and credit can improve upon a standard Taylor rule. The paper closest to ours in terms of modelling choice is Gelain and Ilbas (2014), which looks at optimal simple monetary and macroprudential rules in a version of the Gertler and Karadi (2011) model estimated on U.S. data. Their paper considers the gains that might be achieved from setting policy instruments in a coordinated manner.

Second, several papers study how financial frictions affect the design of monetary policy by analysing optimal monetary policy under commitment when policymakers aim to maximise social welfare or an approximation thereof. Monacelli (2008) and De Fiore et al. (2011) analyse the non-linear Ramsey problem, while other papers, including Carlstrom et al. (2010), De Fiore and Tristani (2013), and Andrés et al. (2013) use the linear-quadratic approach. This approach makes use of an approximation to social welfare which has the advantage of shedding light on what policymakers' stabilisation goals are. It turns out that under financial frictions the central bank should no longer only care about the stabilisation of inflation and the welfare relevant output gap. The presence of financial frictions gives rise to an additional stabilisation goal whose exact format depends on the way in which financial frictions are modeled.

The remainder of this paper proceeds as follows. In section 3.2, we introduce the macroeconomic model we use in our analysis, and give an overview of its equilibrium conditions. We detail the data and estimation method we use, and provide an overview of the key estimation results. Section 3.3 discusses how we operationalise a policy of leaning against the wind, in the context of an optimal monetary policy exercise. It further explains how the policy frontiers that form the main results of the paper are computed. Policy frontiers and associated summary statistics on policy tradeoffs are presented in section 3.4, and section 3.5 concludes.

3.2 An estimated DSGE model with financial frictions

The goal of our analysis is to provide a quantitative guidance on the menu of outcomes that monetary policy can deliver in an economy characterised by financial frictions. The model we adopt for this purpose is a version of that proposed by Gertler and Karadi (2011), which we estimate on U.K. data. Its core is a standard sticky price model, with multiple sources of real frictions. A financial sector intermediates funds between households, who have surplus savings, and firms, who have projects in need of financing. The intermediation process is afflicted by a financial friction, as it is managed by a set of agents called 'bankers' that are subject to moral hazard problem (described below). Awareness of this problem leads to an endogenous limit on the extent of funding that households will extend to intermediaries, and thus on bank credit and leverage.

3.2.1 The DSGE model

In this section, we present the equilibrium conditions of the Gertler and Karadi model, after linearisation around the deterministic steady state. A hat over a variable denotes log deviation from steady state, while an over-bar denotes a steady state value.[7] A full set of model equations can be found in Appendix C.1.

The banking sector

On the asset side of their balance sheets, banks hold direct claims on the capital employed by firms ('primary securities', denoted $\hat{s}_t$) which have mark-to-market value $\hat{q}_t$ (also the relative price of capital goods). They fund their assets with a fixed deposit liability ($\hat{d}_t$), and internal equity ($\hat{n}_t$, 'net worth'). Their balance sheet identity is thus:

$$\hat{q}_t + \hat{s}_t = (\overline{D}/\overline{S})\hat{d}_t + (\overline{N}/\overline{S})\hat{n}_t \tag{3.1}$$

where the ratio of net worth to assets $\overline{N}/\overline{S}$ is the bank's (inverse) leverage ratio. Banks are ultimately owned by households. They are run by household members known as 'bankers'. When they start a bank, bankers receive a transfer of resources from their 'home' household in proportion ξ to existing bank assets, which forms their initial inside equity stake. Over time, the bank accumulates additional internal funds from the spread earned between asset returns ($\hat{r}_{s,t}$) and the risk free interest paid on deposits ($\hat{r}_t$). Bankers are replaced by new management with probability $(1 - \sigma)$ each quarter, whereupon exiting bankers transfer their accumulated funds back to the home household. After aggregating over continuing and entering

[7] In this section, and in the section on optimal monetary policy, we assume a steady state rate of inflation of zero.

bankers, banking system net worth can be shown to evolve as:

$$\hat{n}_t = (\sigma + \xi)(\overline{S}/\overline{N})\overline{R}_s(\hat{q}_{t-1} + \hat{s}_{t-1} + \hat{r}_{s,t}) - \sigma(\overline{D}/\overline{N})\overline{R}(\hat{r}_{t-1} + \hat{d}_{t-1}) - \overline{n}\hat{\psi}_t^N \tag{3.2}$$

where $\hat{\psi}_t^N$ is an exogenous shock to net worth.[8] In choosing the structure of its balance sheet, the bank is constrained by the behaviour of depositors.[9] They place limits on the quantity of deposit funding they are willing to extend because they are aware that bankers can take a hidden action to divert resources for their own benefit, an action which will result in the bank going out of business. The extent of the private benefits bankers can enjoy is proportional (θ) to the overall size of their balance sheet. Incentive compatibility on the part of bankers requires that the 'going concern' value of the bank—the expected present value of future profits if remaining in business—exceeds the 'gone concern' or liquidation value of the bank. The shadow value of a marginal relaxation of this incentive constraint ($\hat{\lambda}_t$) thus depends on the spread ($\hat{\mu}_t$ when valued in banker utility terms) that can be earned from leveraging the relaxation into additional loans:

$$\hat{\lambda}_t = \frac{\theta}{\theta - \overline{\mu}}\hat{\mu}_t \tag{3.3}$$

An additional unit of net worth relaxes the incentive constraint, raising the future value of the bank for continuing bankers in proportion to the return on assets ($\hat{v}_t - \hat{q}_t$, in banker utility terms). But if the banker randomly exits it may also be consumed. Averaging over these contingencies, the shadow

[8]The shock effects an exogenous transfer from bankers to households, and as such is purely redistributive.

[9]It is customary to think of depositors as belonging to households other than that of the banker herself.

value of a unit of net worth ($\hat{\Omega}_t$) is:

$$\overline{\Omega}\hat{\Omega}_t = \sigma\overline{\nu}(1+\overline{\lambda})(\hat{\nu}_t - \hat{q}_t) + \sigma\overline{\lambda}(\overline{\nu}-\theta)\hat{\lambda}_t \tag{3.4}$$

Future returns are discounted according to the household's stochastic discount factor ($\hat{\lambda}_{t+1}$), but with an adjustment to reflect the additional shadow value of accumulated returns via net worth:

$$\hat{\nu}_t - \hat{q}_t = \mathbb{E}_t\hat{\Lambda}_{t+1} + \mathbb{E}_t\hat{\Omega}_{t+1} + \mathbb{E}_t\hat{r}_{s,t+1} \tag{3.5}$$

$$\hat{\mu}_t = \hat{\Lambda}_{t+1} + \mathbb{E}_t\hat{\Omega}_{t+1} + (\overline{R}_s\mathbb{E}_t\hat{r}_{s,t+1} - \overline{R}\hat{r}_t)/(\overline{R}_s - \overline{R}) \tag{3.6}$$

Finally, the volume of deposits banks can raise, given their net worth, is given by:

$$(\theta-\overline{\mu})\hat{d}_t - (\overline{\nu}-\theta)(\overline{N}/\overline{D})\hat{n}_t = \overline{\mu}\hat{\mu}_t + \overline{\nu}(\overline{N}/\overline{D})(\hat{\nu}_t - \hat{q}_t) \tag{3.7}$$

This completes the description of the banking sector. Although necessarily somewhat stylized, the Gertler and Karadi model of banking captures some important insights. First, banks earn carry profits from maturity transformation (but have no non-interest income). Second, the simplifying assumption that there is a single class of non-defaultable claim on firms captures the most economically relevant aspect of banks' portfolio problem—that they are exposed to gains and losses on their assets—while bypassing the complexities of modelling default directly. Third, bank equity is held internally, and cannot be actively raised response to shocks. Rather, it must be rebuilt slowly via retained earnings. This assumption captures the essential aspects of the debt overhang problem banks face when attempting to raise external funding in a pinch.

The macroeconomy

We now briefly reprise the linearised equilibrium conditions for the rest of the macroeconomy. Households have habit persistence of degree h in consumption, making their marginal utility ($\hat{u}_{ct}$):

$$\hat{u}_{c,t} = -\frac{1}{1-h}\hat{c}_t + \frac{h}{1-h}\hat{c}_{t-1} \tag{3.8}$$

Their preferences are subject to a random disturbances $\hat{\psi}_t^R$ which we label a 'risk shock' below. Households stochastic discount factor is therefore:

$$\hat{\Lambda}_t = \hat{\psi}_t^R + \hat{u}_{c,t} - \hat{u}_{c,t-1} \tag{3.9}$$

which is related to real rates by:

$$-\mathbb{E}_t\hat{\Lambda}_{t+1} = \hat{r}_t \tag{3.10}$$

With separable preferences, labour supply is given by

$$\hat{w}_t + \hat{u}_{c,t} = \varphi\hat{l}_t \tag{3.11}$$

where $\hat{l}_t$ are labour hours and φ is the reciprocal of the Frisch elasticity of labour supply. The economy's aggregate goods output ($\hat{y}_t$) is produced by monopolistically competitive firms that operate a Cobb-Douglas technology in labour and physical capital ($\hat{k}_t$), subject to productivity disturbances

($\hat{a}_t$):

$$\hat{y}_t = \hat{a}_t + \alpha\hat{k}_{t-1} + (1-\alpha)\hat{l}_t \tag{3.12}$$

where α is the elasticity of output with respect to capital. Factor markets are competitive, and firms' factor demand schedules are given by:

$$\hat{z}_t = \hat{\text{mc}}_t + \hat{y}_t - \hat{k}_{t-1} \tag{3.13}$$

$$\hat{w}_t = \hat{\text{mc}}_t + \hat{y}_t - \hat{l}_t \tag{3.14}$$

where $\hat{z}_t$ is the capital rental rate, $\hat{w}_t$ is the real wage, and $\hat{\text{mc}}_t$ is real marginal cost. Capital goods producing firms face an adjustment cost that is quadratic in the rate of investment ($\hat{i}_t$), with parameter κ. The price of capital relative to goods is then given by:

$$\hat{q}_t + \hat{\psi}_t^I = \kappa(\hat{i}_t - \hat{i}_{t-1}) - \beta\kappa(\mathbb{E}_t\hat{i}_{t+1} - \hat{i}_t) \tag{3.15}$$

where β is the household's subjective discount factor, and $\hat{\psi}_t^I$ is an investment-specific technology shock (Justiniano et al., 2010). Physical capital depreciates at rate δ per quarter, so its law of motion is given by:

$$\hat{k}_t = (1-\delta)\hat{k}_{t-1} + \delta(\hat{i}_t + \hat{\psi}_t^I) \tag{3.16}$$

Finally on the real side, the aggregate resource constraint and clearing in the loan market require:

$$\hat{y}_t = (\overline{C}/\overline{Y})\hat{c}_t + (\overline{I}/\overline{Y})\hat{i}_t + (\overline{G}/\overline{Y})\hat{g}_t \tag{3.17}$$

$$\hat{k}_t = \hat{s}_t \tag{3.18}$$

where $\hat{g}_t$ is an exogenous shock to government consumption.

Turning to the nominal side of the economy and monetary policy, firms are permitted to reset the prices they charge optimally with with probability $1-\gamma$. The proportion γ of firms that cannot reset their price are permitted to index to lagged inflation (with degree of indexation ι). The headline inflation rate is thus:

$$\gamma\hat{\pi}_t - \gamma\iota\hat{\pi}_{t-1} = (1-\gamma)\hat{\pi}_t^* \tag{3.19}$$

where $\hat{\pi}_t^*$ is reset price inflation, defined by the following recursive relations:

$$\hat{\pi}_t^* = \hat{\Gamma}_{1,t} - \hat{\Gamma}_{2,t} \tag{3.20}$$

$$\hat{\Gamma}_{1,t} = (1-\gamma\beta)(\hat{\mathrm{mc}}_t + \hat{y}_t) + \gamma\beta\mathbb{E}_t(\hat{\Lambda}_{t+1} + \varepsilon\hat{\pi}_{t+1} - \iota\varepsilon\hat{\pi}_t + \hat{\Gamma}_{1,t+1}) \tag{3.21}$$

$$\hat{\Gamma}_{2,t} = (1-\gamma\beta)\hat{y}_t + \gamma\beta\mathbb{E}_t[\hat{\Lambda}_{t+1} + (\varepsilon-1)\hat{\pi}_{t+1} - \iota(\varepsilon-1)\hat{\pi}_t + \hat{\Gamma}_{2,t+1}] \tag{3.22}$$

The Fisher relation linking nominal and real rates is:

$$\hat{f}_t = \hat{r}_t + \mathbb{E}_t\hat{\pi}_{t+1} \tag{3.23}$$

where $\hat{f}_t$ denotes nominal short term rates, that are taken to be the monetary policy instrument. Finally, in the version of model that we estimate, monetary policy is assumed to follow the simple instrument rule:

$$\hat{f}_t = \rho\hat{f}_{t-1} + (1-\rho)[\phi_\pi\hat{\pi}_t + \phi_y\hat{y}_t] + \hat{\psi}_t^M \tag{3.24}$$

where $\hat{\psi}_t^M$ is a monetary policy shock. In the optimal policy exercise, the instrument rule is implicitly replaced by an optimal targeting rule.

3.2.2 Data and estimation

The model presented is estimated with Bayesian methods on five quarterly U.K. observable variables: real GDP, real investment, inflation, credit spreads and the Bank of England's shadow policy rate. (Log) real GDP and investment are detrended using the one-sided Hodrick-Prescott filter.[10] Inflation is the first-difference of the log consumer price index. Corporate credit spreads is provided by the Bank of America Merrill Lynch, which are option-adjusted investment-grade U.K. corporate bond yields minus the government bond yield at the same maturity. This is available from 1997 onwards. Before that, we use the yields from Global Financial Data. We use the the shadow rate as the observable of the risk-free and policy rate. It is simply the Bank Rate before the beginning of unconventional policy measures, and after that is Bank Rate augmented to include a Bank of England in-house estimate of the equivalent Bank Rate that would mimic the effects of quantitative easing.[11] This is to take into account the effects of unconventional policies, without explicitly modelling asset purchases or the zero lower bound. Inflation, credit spreads and the shadow rate are

[10]We choose the one-sided HP filter (instead of the more conventional two-sided) for two reasons. Firstly, a two-sided filter would produce a remarkable positive output gap before the Great Recession. This is not reconcilable with the observation that inflation was on target during the same period. Secondly, as the likelihood is extracted using the Kalman filter (which uses current and past data), our detrended series should not contain information about future data.

[11]The shadow rate is derived by computing a sequence of unanticipated monetary policy shocks to match the time series for the estimated effect of QE on GBP using estimates from [joyce et al] – see also Section 8.4 of Burgess et al. (2013). The underlying assumption that underpins this approach is that QE is a close substitute as a monetary policy instrument to Bank Rate such that the zero lower bound was not an effective constraint on monetary policy over the period in question.

demeaned.

The sample is from 1992Q1 to 2015Q1. This sample length was selected in order to avoid estimation problems due to changes in the monetary regime. A random-walk Metropolis-Hastings algorithm with two Markov chains of 300,000 draws each (with the first 120,000 draws discarded) was used to sample the posterior distribution. Convergence of the chains were tested by the Brooks and Gelman (1998) diagnostic statistics. The analysis in the subsequent sections of this paper will use policy under commitment, which means that there will no longer be monetary policy shocks. However, we elected to estimate in monetary policy shocks because while a Taylor rule is a reasonable approximation to the behaviour of monetary policy, it is not a complete description. Therefore, if we estimate the model without monetary policy shocks (or in other words, calibrate the standard deviation of the innovations to zero), it will be forced to fit the Taylor rule exactly, which may bias the estimates of the structural parameters that we are interested in.

In addition to monetary policy shocks, we have productivity, investment-specific technology, government spending, risk-premium and bank net worth shocks. Productivity shocks are our main supply shock. Given our set of observables, labour supply and markup shocks are observationally equivalent to a productivity shock. Investment-specific technology shocks are shocks to investment demand. This is a closed-economy model, so government spending is lumped together with effects of external trade together, and assumed to be exogenous. Risk-premium shocks act as demand shocks to the IS curve. Lastly, shocks to bank net worth is a financial shock, which reduces the banking sector's ability to extend loans and therefore curbs firm investment.

Calibration

We calibrate the model parameters that govern the steady state of the model, and thus the detrended data would not have much information about. First of the core macro parameters, β is calibrated to 0.99, corresponding to an annualised steady state policy rate of 4%. This also closely matches the average shadow rate in the sample of 3.8%. The depreciation rate δ is calibrated to 0.025, the constant risk aversion coefficient to 3, the capital share α to 0.33 and the elasticity of substitution across consumption goods ε to 6, all literature standard values. The disutility of labour χ is set so that the steady state hours worked is 1. We also calibrate the Frisch elasticity of labour supply to 3, given that we do not use any labour market observables. Lastly, we set the proportion of government spending to GDP to 27.3%, which matches the sample average of government spending, plus net exports. Thus, we assume government spending and net exports as completely exogenous, as we have a closed economy.

For the financial sector, we have two targets: credit spreads and leverage ratio of the whole banking sector. The calibration target for credit spreads is the sample average of the data, of 0.392% at quarterly frequency. We calibrate the survival rate of banks σ to 0.94, following Villa and Yang (2011) who estimated the Gertler and Karadi (2011) model on U.K. data. Raw leverage data of U.K. banks is in excess of 11. However, contained within are many gross positions to other financial institutions, while we only would like to capture their lending capacity to the real economy (less than a fifth of banks' assets consists of loans to households and firms).

Thus, we elect to match the leverage ratio to a more conservative number of 5. These two targets are used to calibrate the diversion parameter θ and the transfer rate of households to banks ξ.

Prior specification

Following Smets and Wouters (2007), the priors of the exogenous shock processes are harmonised across the different shocks, with a fairly uninformative prior. The standard errors of the innovations follow an inverse Gamma distribution with a mean of 0.1 and standard deviation of 2. The AR(1) parameters of the corresponding shocks, where appropriate, has a Beta distribution with a mean of 0.5 and standard deviation of 0.2. Monetary policy and bank net worth shocks are assumed to be completely transitory, and thus have no AR(1) coefficients. However, they still could have persistent effects, as there is interest rate smoothing and net worth is accumulated slowly as a state variable.

The priors describing the monetary policy rule are taken from COMPASS, the Bank of England's primary DSGE model (Burgess et al., 2013). The response to inflation is normally-distributed with a mean of 1.5 and standard deviation of 0.125 (also the prior in Smets and Wouters (2007)), while the response to output deviations from the steady state is normally distributed with a mean of 0.125 and standard deviation of 0.075. The degree of interest rate smoothing is assumed to have a Beta distribution, with a mean of 0.8 and standard deviation of 0.2. This is to incorporate our prior knowledge that policymakers smooth changes to avoid unnecessary interest rate volatility.

The priors of the structural parameters incorporate information from

	Prior			Posterior			
	Dist.	Mean	SD	Mean	Mode	SD	90% HPD
ϕ	Beta	0.75	0.1	0.84	0.84	0.01	[0.82 0.86]
ι	Beta	0.25	0.075	0.23	0.14	0.09	[0.09 0.37]
h	Beta	0.7	0.15	0.94	0.95	0.02	[0.90 0.98]
κ	Gamma	5.85	0.25	5.76	5.67	0.25	[5.36 6.17]
ϕ_π	Normal	1.5	0.125	1.46	1.40	0.13	[1.24 1.68]
ϕ_y	Normal	0.125	0.075	0.33	0.34	0.05	[0.24 0.42]
ρ	Beta	0.8	0.2	0.75	0.76	0.03	[0.70 0.80]

Note: ϕ = Calvo parameter for prices, ι = degree of price indexation, h = degree of external habit formation, κ= investment adjustment costs, ϕ_π = Taylor rule inflation response, ϕ_y = Taylor rule output response and ρ = interest rate smoothing.

Table 3.1. Prior and posterior distribution of structural parameters

previous empirical studies, as much as possible, and if not, priors from previous literature. The degree of price stickiness (the Calvo parameter) is assumed to have a Beta distribution with a mean of 0.75 and standard deviation of 0.1. This matches the micro-data on duration of individual prices that contribute to the Consumer Price Index, as analysed in Bunn and Ellis (2011). The external habit formation parameter has a Beta distribution, with a mean of 0.7 and standard deviation of 0.15. This is approximately in the middle of the estimates surveyed in Harrison and Oomen (2010). For price indexation, we follow COMPASS again to have a Beta distribution with a mean 0.25, standard deviation of 0.075. In investment adjustment costs, we follow Villa and Yang (2011) to a Gamma distribution, with mean 5.85 and standard deviation 0.25.

Posterior estimates of the parameters

Tables (3.1) and (3.2) show the central tendencies and the 90% highest posterior density credible interval of the posterior distribution, simulated as

	Prior			Posterior			
	Dist.	Mean	SD	Mean	Mode	SD	90% HPD
ρ_R	Beta	0.5	0.2	0.27	0.27	0.11	[0.05 0.34]
ρ_A	Beta	0.5	0.2	0.35	0.36	0.11	[0.18 0.52]
ρ_I	Beta	0.5	0.2	0.57	0.58	0.06	[0.48 0.67]
ρ_G	Beta	0.5	0.2	0.72	0.69	0.08	[0.59 0.85]
σ_R	Inv. Gamma	0.1	2.0	0.035	0.031	0.008	[0.021 0.049]
σ_A	Inv. Gamma	0.1	2.0	0.034	0.033	0.007	[0.023 0.045]
σ_I	Inv. Gamma	0.1	2.0	0.020	0.020	0.002	[0.018 0.023]
σ_G	Inv. Gamma	0.1	2.0	0.019	0.019	0.001	[0.016 0.021]
σ_N	Inv. Gamma	0.1	2.0	0.036	0.034	0.003	[0.032 0.041]
σ_M	Inv. Gamma	0.1	2.0	0.009	0.009	0.001	[0.008 0.010]

Note: The shocks are denoted by R = risk premium, A = productivity, I = investment-specific technology, G = government spending and external trade, N = bank net worth and M = monetary policy.

Table 3.2. Prior and posterior distribution of forcing processes

according to the aforementioned Bayesian estimation procedure. A few results are particularly noteworthy in relation of our aim to estimate the frontiers under optimal commitment.

The estimate of the Calvo parameter is notably high, and statistically significantly higher than the prior mean. This implies a flat Phillips curve. The posterior mode for price indexation is about half of the prior mean, albeit still remaining inside the 90% credible interval. The degree of price indexation affects how much current inflation is affected by past inflation (which cannot be changed), versus expectations of future inflation (which can be influenced under commitment by the policymaker).

The habit formation parameter is materially higher than the prior mean. This is the opposite to COMPASS, which finds a lower value than their prior, and higher than the survey evidence in Harrison and Oomen (2010). This is likely because COMPASS has rule-of-thumb consumers that has a similar effect as increasing habit formation, and that we did not use consumption data directly. Also note that, like COMPASS, the model does not identify investment adjustments costs very well.

The estimates of the standard deviation of the exogenous shocks are much smaller than the prior mean, and importantly, with much tighter HPD intervals relative to the loose priors.

3.3 Construction of policy frontiers

In this section we describe how the efficient policy frontier between the volatility of output and inflation is computed. The perspective we adopt is that of 'optimal' monetary policy under commitment. Commitment is an important benchmark, because it represents the best possible outcomes that policymakers can achieve. Adopting this perspective has the advantages that, firstly, policymakers are treated as optimizing agents, symmetrically with other agents in the model. Secondly, the policy design question is disciplined by requiring us to explicitly specify policy objectives in advance. A natural definition of LATW is then that stabilisation of some financial variable is an explicit goal of policy, as we now explain.

3.3.1 Leaning against the wind as a policy objective

As is standard, we take the *ad hoc* period loss function that summarises the mandate given to monetary policymakers to be quadratic in inflation and output, with relative weight ω on inflation. In addition, we allow for LATW by including a weight ς on a range of financial variables, denoted

$\hat{x}_t$, which are defined below:

$$L_t = \varsigma(\omega\hat{\pi}_t^2 + [1-\omega]\hat{y}_t^2) + (1-\varsigma)\hat{x}_t^2 \tag{3.25}$$

As ω varies in the range from $(0,1]$, relatively more weight is placed on inflation *versus* output stabilisation. When $\varsigma = 1$, the policymaker places no weight on financial objectives. This is the standard no-leaning-against-the-wind case. When $\varsigma < 1$, we interpret (3.25) as implying that the policymaker's mandate involves some degree of LATW.

It is a good time to remind the reader that we do not provide normative prescriptions regarding the conduct of monetary policy under financial frictions. The exercise that we perform only obtains the set of feasible outcomes that a policymaker can choose from, under commitment, rather than selecting *which* of those outcomes is optimal from a social welfare perspective. *Ad hoc* objective functions similar to (3.25) have been adopted in related work by *inter alia* Angelini et al. (2014), Gambacorta and Signoretti (2014) and Gelain and Ilbas (2014), although these papers further restrict themselves to consideration of *ad hoc* simple instrument rules. A noteworthy paper is Andrés et al. (2013), who have found that it is optimal for a social planner to stabilise variables other than inflation and output gap. This is due to the need of collateral and the existence of inefficient risk sharing between households and entrepreneurs, both resulting from a collateral constraint financial friction. The analogous counterpart in our moral hazard framework is to stabilise bank leverage and credit spreads, two of the variables that we study. The other two – credit growth and credit-to-GDP ratio – are also studied as they commonly feature in the range of financial variables that central banks typically consider as part of their financial sector risk assessments.

A common definition identifies LATW with the inclusion of some financial variable in a simple instrument rule for the policy interest rate. But arguably, policy should (and does) respond to financial variables even under standard policy objectives, for example because they forecast future output and inflation. In the class of models we study here, a common finding in the literature is that there are a wide range of circumstances under which responding to financial variables does improve outcomes. However, as the benchmark is an arbitrary sub-optimal instrument rule, this finding is open to a range of interpretations.[12]

Defining LATW in terms of policy *objectives* has some advantages relative to the alternatives. A common alternative definition, given in this case by Svensson (2011, pp. 1293–4), is that:

> central banks should raise the interest rate more than what appears to be warranted by inflation and resource utilisation to counter rapid credit growth and rising asset prices

A drawback of this definition is that it defines the LATW policy in terms of equilibrium outcomes. As a result, the LATW property so described need not hold along every policy path, in response to every shock, making it

[12]Svensson (2011, p. 1294) notes: 'Sometimes it is not quite clear whether advocates of leaning against the wind mean that credit growth and asset prices should be considered targets and enter the explicit or implicit loss functions alongside inflation and output utilisation, or whether they mean that credit growth and assets prices should still be considered just indicators and are emphasised only because credit growth and asset prices may have potential negative effects on inflation and resource utilisation at a longer horizon. In the latter case, leaning against the wind is... completely consistent with flexible inflation targeting.' As we emphasise here, we identify LATW with monetary policy having specific regard for financial variables *as policy goals*.

somewhat ambiguous.[13]

3.3.2 Optimal control and the policy frontier

The optimal policy problem at some initial date 0 is to maximise by choice of the policy instrument (nominal interest rates) $\{f_t\}_0^\infty$ the intertemporal loss function:

$$\mathcal{L}_0 = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t L_t(\hat{\pi}_t, \hat{y}_t, \hat{x}_t)$$

subject to the equilibrium conditions of the economy given by (3.1)–(3.23). The resulting set of first order conditions, which include the original 23 equilibrium conditions, five forcing processes (monetary policy shocks removed) and additional equations describing the evolution of the Lagrange multipliers, are solved numerically for the steady state.[14] The equilibrium laws of motion for the endogenous variables under optimal policy are then found using standard techniques for linear rational expectations models (see Dennis, 2007, for example).[15] All parameters in Table 3.1 and 3.2, including those for the forcing processes, are set to their estimated modal posterior values.

The efficient frontier for a given degree of LATW (including $\varsigma = 1$) is traced out by solving the optimal control problem just described as the weight on inflation ω varies in the range $(0, 1]$. For a given ω, the elasticity of the frontier at each point is rate at which inflation and output volatility

[13] The interest rate might initially be higher under LATW, but lower later; or the commitment to a more-vigorous response to asset prices might lead to lower rates, and so on.

[14] As the monetary policy rule adopted for estimation is dropped in the optimal policy exercise, the monetary policy shock is not counted amongst the exogenous driving forces.

[15] Dynare code that implements the solution of the model under optimal commitment policy is available on request from the authors.

can be traded off against each other.[16]

3.4 Main results

In this section, we present our main results on how the shape and position of the efficient policy frontier are affected by a policy of LATW. We consider four financial variables against which policymakers may wish to lean: credit growth, the credit-to-GDP ratio, credit spreads, and bank leverage.[17] For each variable, we compute the efficient frontier under the all estimated structural shocks (except monetary policy), and conditional on each shock individually, for the standard objective ($\varsigma = 1$) and for different degrees of LATW. Leaning 'a bit' corresponds to a choice of $\varsigma < 1$ that reduces the volatility of a given financial variable by 10%; leaning 'a lot' reduces financial volatility by 50% (both relative to the 'all shocks' baseline with $\varsigma = 1, \omega = 0.5$).

Efficient inflation-output frontiers when policy leans against the credit-to-GDP ratio and the spread are shown in figures 3.1 and 3.2 respectively. The frontier closest to the origin in inflation-output space corresponds to the standard no-LATW case. Frontiers that lie further to the north-east correspond to higher degrees of LATW. It is immediately apparent that a consequence of monetary policymakers LATW – by including either credit-

[16]In the special case $\varsigma = 0$, $\omega = 0.5$, the tradeoff is one-for-one in *variance* space. With policymaker preferences so defined, the marginal rate of substitution between their objectives is -1, which at the optimum is also the economy's marginal rate of transformation. In conventionally-reported *volatility* (standard deviation) space, an adjustment is required for the relative volatilities of output and inflation. In addition, we plot $\omega \in [0.2, 0.9]$ to avoid implausible extreme values in the charts.

[17]In our model, banking variables are measured at their 'mark-to-market' values, rather than at book value. In practice, banks report a large portion of their assets at book value, in which case policy be unable to target the measure of leverage we use in this paper.

to-GDP or loan-deposit spreads in their loss function – is that they face a strictly worse menu of inflation-output volatility choices, and that the deterioration is economically significant. In the 'all shocks' case, halving volatility in the credit-to-GDP ratio entails an increase in output volatility of around 0.5 percentage points. Halving the volatility of spreads is less costly, but still raises output volatility by 0.1-0.2 percentage points. Interestingly, for a given weight on inflation stabilisation, LATW tends to reduce the variability of inflation (although the overall position of the frontier, as explained, is less favourable).

In the remainder of this section, we will focus on three distinct aspects of these frontiers: (i) the *elasticity* of the frontiers, or the implied inflation-output trade-off, at a standard mid-point corresponding to equal weights on inflation and output; (ii) their *location*, or the extent to which the cost in terms of inflation and output volatility of per-unit reductions in financial volatility depends on LATW; (c) how financial volatility is affected by moves *along* a given frontier, that is, by the relative weight on inflation versus output stabilisation.

3.4.1 The slope of the policy frontier

The percentage change in inflation volatility following a unit increase in output volatility along the efficient frontiers – i.e. the policy tradeoffs— are summarised in Table 3.3. The elasticities are calculated for the case in which the relative weight on output and inflation in the policymaker's loss function are equal ($\omega = 0.5$ in equation 3.25), which in most cases corresponds to a point roughly in the centre of each plotted frontier. Each

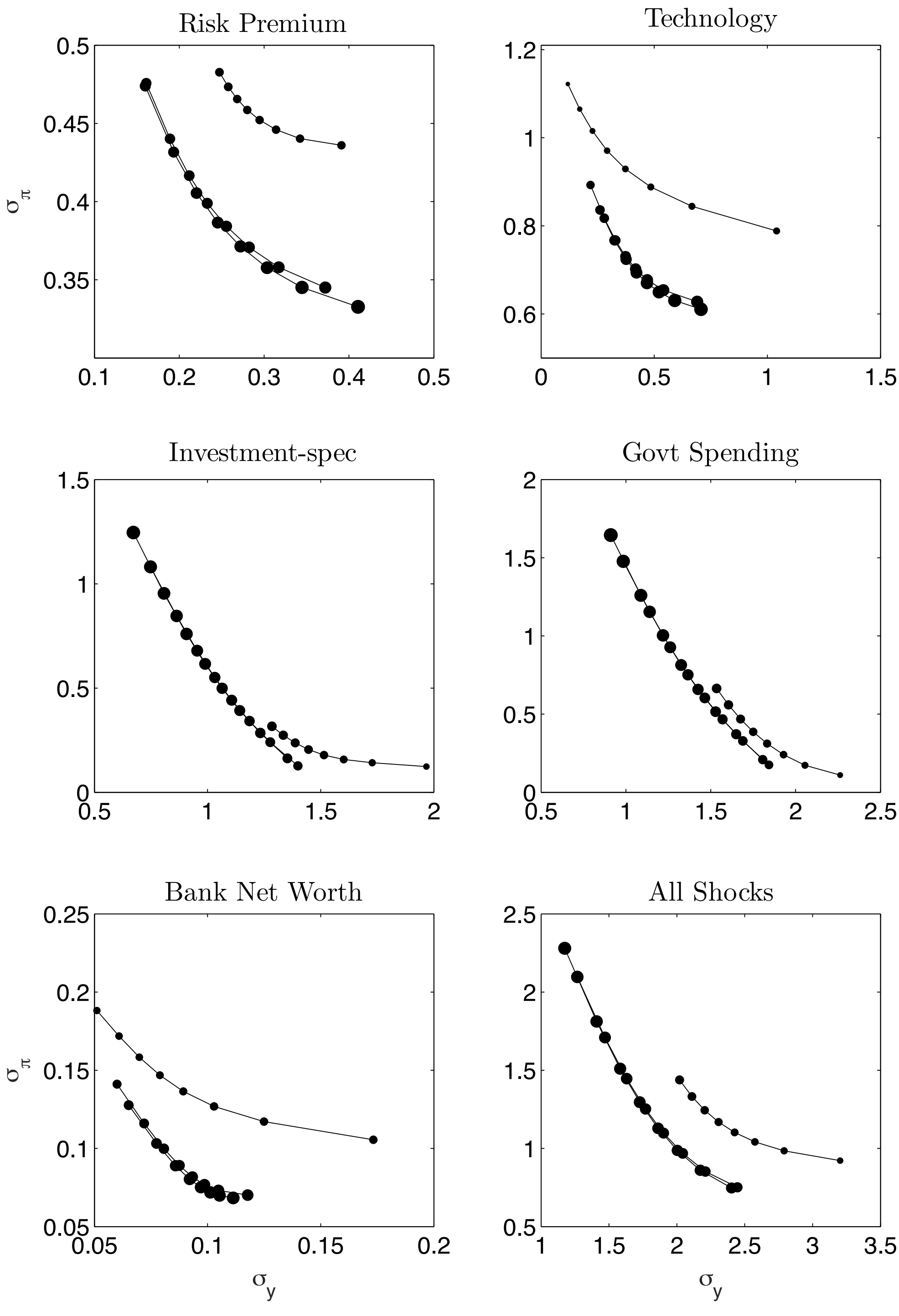


Figure 3.1. Efficient policy frontiers when policy leans against the credit-to-GDP ratio

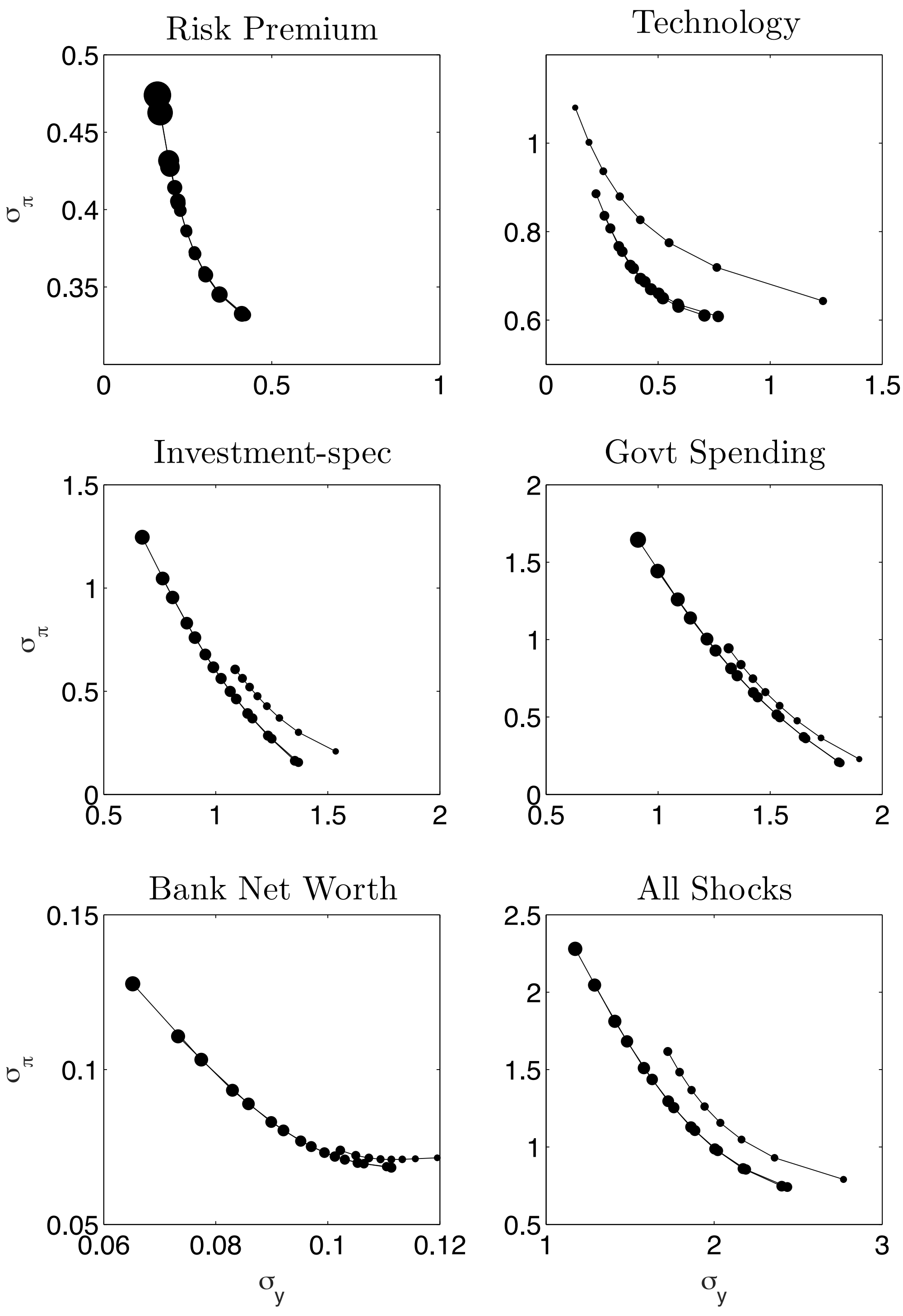


Figure 3.2. Efficient policy frontiers when policy leans against the loan-deposit spread

row of the table shows the tradeoff conditional on the estimated structural shock named in the first column, except for the last row, in which the unconditional tradeoff is reported.[18]

The second column gives the tradeoffs when policymakers do not LATW. On average, inflation and output volatility can be traded off at a rate just under two-for-one; a 1 percent increase in output volatility lowers inflation volatility by 1.8 percent. But it is immediately evident that some shocks lead inflation stabilisation to have a much higher output cost than others (entries closer to zero). For example, the tradeoff conditioned on productivity shocks is such that increasing output volatility by one percent results in only a 0.4 percent reduction in inflation volatility. Conditional on investment-specific technology shocks, the equivalent reduction is 2.7 percent.

Columns 3 through 6 show the effect of LATW on the inflation-output tradeoff. Each column reports the impact of 'leaning' against a different financial variable, either 'a bit' or 'a lot'. The main message that emerges is that a bit of LATW has hardly any impact on the elasticity of the policy frontier, irrespective of which financial variable the policymaker chooses to lean against. This is true both for the unconditional frontier, and for those conditioned on particular shocks. That the tradeoff is roughly unaffected does not, of course, imply that LATW is costless, as we discussed above. But it does indicate that one important aspect of policy choice is robust to some LATW.

On the other hand, a lot of LATW does change things quite sub-

[18] Recall that shocks to the estimated monetary policy rule are omitted in the optimal policy exercise.

		Leaning against...							
	No	ΔCredit		Credit:GDP		Spreads		Leverage	
Shock to...	LATW	a bit	a lot	a bit	a lot	a bit	a lot	a bit	a lot
Risk	-0.4	-0.4	-0.4	-0.5	-0.3	-0.4	-0.4	-0.4	-0.4
Productivity	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4
Investment	-2.7	-2.6	-2.0	-2.5	-0.7	-2.5	-1.9	-2.5	-1.9
Government	-2.7	-2.7	-2.3	-2.6	-1.6	-2.6	-2.4	-2.6	-2.4
Net worth	-1.4	-1.5	-1.3	-1.6	-1.3	-1.2	-0.1	-1.2	-0.1
All shocks	-1.8	-1.8	-1.4	-1.7	-0.9	-1.7	-1.7	-1.7	-1.7

Table 3.3. The inflation-output tradeoff in an estimated model with financial frictions, with and without leaning against the wind

Note: Table entries are the percentage change in inflation volatility with respect to a one percent change in output volatility on the optimal policy frontier, for the model described in Section 3.2. Equal weight is placed on inflation and output ($\omega = 1/2$ in equation 3.25). In rows, we show the tradeoffs conditional on each of the shocks named in column 1. In column 2, we show the 'No LATW' case, corresponding to $\varsigma = 1$ in equation (3.25). In columns 3–6 we show the case $\varsigma < 1$ in which the financial variable x_t in equation (3.25) is one of the named alternatives. Leaning against variable x_t 'a bit' means reducing the volatility of that variable by 10% (relative to the 'all shocks' baseline with $\omega = 1/2, \varsigma = 1$); leaning against it 'a lot' means reducing its volatility by 50%.

stantially. The slope of the unconditional frontiers become flatter when leaning against credit growth, especially when leaning against the debt-to-GDP ratio. This raises the output cost of inflation stabilisation. The sources of the flatter unconditional tradeoff are the flatter tradeoffs to investment specific technology and government spending shocks. When spreads or leverage are the targets for LATW, the unconditional tradeoffs are roughly unchanged, but the elasticity of the efficient frontier conditional on net worth disturbances falls to almost zero. In this case, directing monetary policy towards the goal of stabilizing financial variables comes at the price of losing the ability to tradeoff stabilisation of inflation and stabilisation of output. This may be worrisome, but does not matter much on average, because net worth shocks are not estimated to be an especially important source of fluctuations.

	Leaning against...							
	ΔCredit		Credit:GDP		Spreads		Leverage	
Shock to...	a bit	a lot	a bit	a lot	a bit	a lot	a bit	a lot
Risk	-0.2	-0.1	-0.4	0.3	0.1	0.2	-0.1	-0.1
Productivity	-0.5	-0.4	-0.7	-0.4	-0.8	-0.4	-0.8	-0.4
Investment	0.2	0.5	0.6	1.0	0.4	0.4	0.4	0.4
Government	0.1	0.3	0.3	0.7	0.2	0.2	0.2	0.2
Net worth	-0.2	-0.1	-0.3	-0.3	0.3	0.4	0.3	0.4
All shocks	-0.0	0.2	0.2	0.7	0.2	0.3	0.2	0.2

Table 3.4. The sensitivity of output volatility to a reduction in financial volatility for different degrees of leaning against the wind

Note: Table entries are the percentage change in output volatility given a one percent reduction in financial volatility on the optimal policy frontiers, for the model described in Section 3.2. Equal weight on inflation and output is assumed ($\omega = 1/2$ in equation 3.25). In rows, we show sensitivities conditional on each of the shocks named in column 1. In columns 2–5 we show the case $\varsigma < 1$ in which the financial variable x_t in equation (3.25) is one of the named alternatives. Leaning against variable x_t 'a bit' means reducing the volatility of that variable by 10% (relative to the 'all shocks' baseline with $\omega = 1/2, \varsigma = 1$); leaning against it 'a lot' means reducing its volatility by 50%.

3.4.2 The location of the policy frontier

In this section we examine the sensitivity of the *location* of the efficient policy frontiers to reductions in financial volatility for different degrees of LATW (and equal weights on output and inflation stabilisation). Tables 3.4 and 3.5 consider output and inflation volatility separately. A positively-signed entry indicates that lower financial volatility goes hand-in-hand with increased macroeconomic volatility; a negatively-signed entry indicates the opposite. A comparison of the two tables makes it apparent that curbing financial volatility *either* has an output cost, *or* an inflation cost, but not both. (The sole exception is that a reduction in financial volatility conditional on risk shocks and leaning 'a lot' against the credit-to-GDP ratio comes at the expense both of higher output and higher inflation volatility.)

The main message of Tables 3.4 and 3.5 is that the marginal cost, in

	Leaning against...							
	ΔCredit		Credit:GDP		Spreads		Leverage	
Shock to...	a bit	a lot	a bit	a lot	a bit	a lot	a bit	a lot
Risk	0.1	0.2	0.2	0.4	-0.1	-0.1	0.0	0.0
Productivity	0.2	0.5	0.3	0.6	0.3	0.5	0.4	0.6
Investment	-0.5	-0.9	-1.4	-1.5	-0.9	-0.5	-0.9	-0.5
Government	-0.2	-0.6	-0.9	-1.1	-0.6	-0.4	-0.6	-0.4
Net worth	0.5	1.1	0.8	1.5	-0.4	-0.2	-0.4	-0.2
All shocks	-0.0	-0.0	-0.3	-0.2	-0.3	-0.1	-0.3	-0.0

Table 3.5. The sensitivity of inflation volatility to a reduction in financial volatility for different degrees of leaning against the wind

Note: Table entries are the percentage change in inflation volatility given a one percent reduction in financial volatility on the optimal policy frontiers, for the model described in Section 3.2. See note to table 3.4.

terms of macroeconomic volatility, of reducing financial volatility is always increasing in the degree of LATW (or, the marginal benefit is reduced). In other words, moving from 'a bit' to 'a lot' of LATW raises the cost (reduces the benefit) of a marginal reduction in financial volatility. This is particularly marked in the case of output volatility, when regard is given to the credit-to-GDP ratio; and inflation volatility, when regard is given to leverage. A general implication of the non-linear nature of the costs associated with LATW, highlighted by the tables, is that the structure of the economy puts limits on the ability of monetary policy to stabilise the macroeconomy, while also stabilizing financial variables. That observation implies that even if monetary policy is used as a first line of defence against financial volatility, other tools – even ones thought less effective, or whose impact is uncertain – might be preferred at the margin.

3.4.3 The inflation-output-financial tradeoff

The efficient policy frontiers in Figures 3.1 and 3.2 contain information on the volatility of financial variables, relative to the base case $\varsigma = 1$ and $\omega = 0.5$ in equation (3.25). This case is indicated by a circular line marker in the centre of the frontier closest to the origin. As we have remarked, there is variation in financial volatility between frontiers; that is, for varying degrees of LATW. But there is also variation within frontiers; that is, where policymakers locate themselves in inflation-output space has an impact on financial volatility.

Consider the case where policy leans against the credit-to-GDP ratio, shown in Figure 3.1. Where 'all shocks' are active, the volatility of credit-to-GDP is 8.9% in the base case. It is evident that, for a given degree of LATW (including none), a higher weight on inflation stabilisation – a south-east move along a given frontier – tends to reduce financial volatility. Note the similar size of the circle at the north-western end of the no LATW frontier and that at the south-eastern end of the outermost frontier; corresponding to an absolute credit-to-GDP volatility of 10.7% and 7.7%, respectively. It is evident that similar reductions in financial volatility are achievable by two different policies: a lot of LATW, while placing a low weight on inflation stabilisation; or no-LATW, while placing a high weight on inflation stabilisation. Examination of the conditional policy frontiers indicates that the source of the shock is again relevant. Investment-specific technology and government spending shocks resemble the 'all shocks' case. But conditional on productivity and risk premium shocks, a higher weight on inflation stabilisation leads to a greater, not lesser, degree of financial volatility.

We turn to the case where policy leans against the loan-to-deposit interest spread, shown in Figure 3.2. The frontiers closest to the origin, pertaining to the no LATW case, are of course identical to those in Figure 3.1. Similar patterns of financial volatility can be observed along the frontiers, with a greater concern for output stabilisation tending to raise financial volatility on average, but the reverse being true in the case of productivity shocks. The main difference appears to lie in the conditional frontier for risk premium shocks. These cause spreads to be very volatile indeed, relative to the baseline, as increased weight is placed on output stabilisation.

3.5 Conclusion

In this paper, we attempt to advance the discussion on the merits or otherwise of augmenting central banks' mandates to stabilise financial variables, commonly known as leaning against the wind (LATW). In particular, our results provide a menu of options that the policymakers can select from, if they wish to lean against the wind with the policy interest rate. We set out how the tradeoff between the traditional objectives of monetary policy is quantitatively affected by LATW, by estimating a standard sticky-price macroeconomic model with financial frictions (Gertler and Karadi, 2011) and computing optimal monetary policy under commitment. We find three main results. Firstly, LATW leads policymakers to face a strictly worse menu of inflation-output volatility choices, and that this deterioration is economically significant. Secondly, the marginal cost in terms of output and inflation volatility, when reducing financial volatility is increasing in the degree of LATW. Thirdly, LATW has effects that depend crucially on the nature of the underlying disturbance, and on the precise variable that policy aims to stabilise.

Appendix A

Competition Effects of Financial Shocks on Business Cycles

A.1 Robustness Checks for VAR

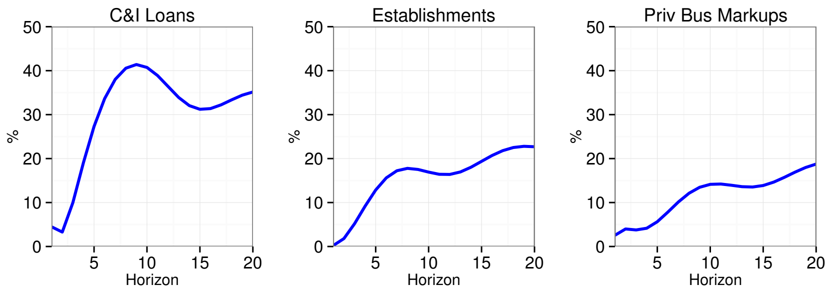


Figure A.1. FEVD to credit supply shocks (HP filtered variables)

Note: The credit contraction shock is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

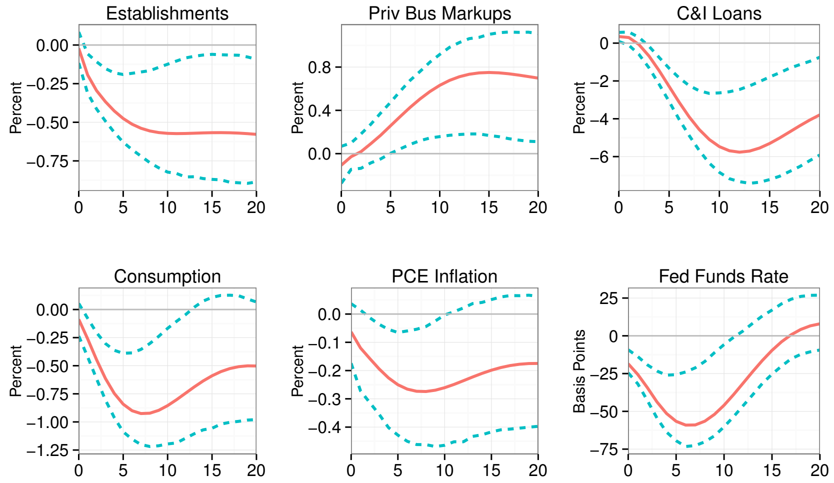


Figure A.2. VAR ordering: $\mathbf{X}_t = [cs_t \; l_t \; N_t \; \mu_t \; c_t \; \pi_t \; r_t]'$

Note: The credit contraction shock is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

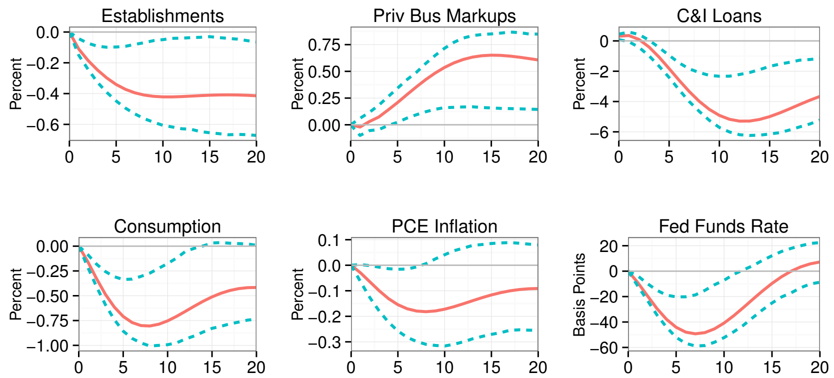


Figure A.3. VAR ordering: $\mathbf{X}_t = [N_t \; \mu_t \; y_t \; \pi_t \; r_t \; l_t \; cs_t \; l_t]'$

Note: The credit contraction shock is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

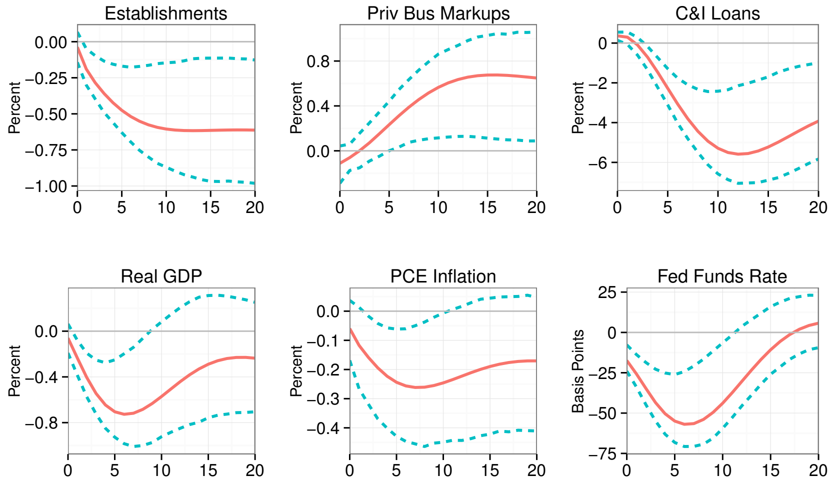


Figure A.4. VAR (with GDP) ordering: $\mathbf{X}_t = [cs_t \; N_t \; \mu_t \; y_t \; \pi_t \; r_t \; l_t]'$

Note: The credit contraction shock is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

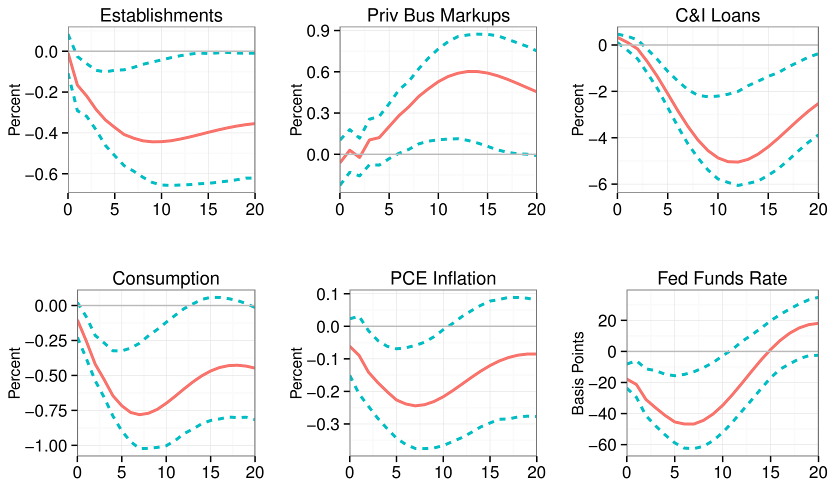


Figure A.5. VAR (with GDP) ordering: $\mathbf{X}_t = [cs_t \; N_t \; \mu_t \; y_t \; \pi_t \; r_t \; l_t]'$

Note: The credit contraction shock is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

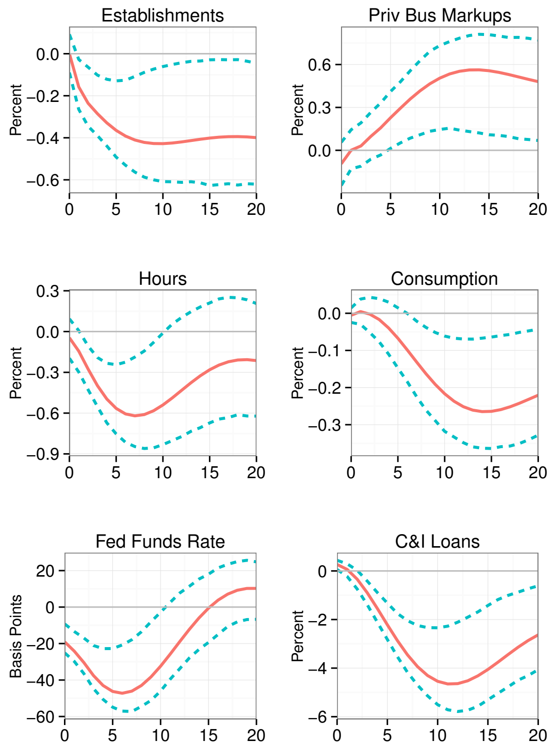


Figure A.6. VAR with labour market: $\mathbf{X}_t = [N_t \; \mu_t \; w_t \; h_t \; c_t \; \pi_t \; r_t \; l_t \; cs_t \; l_t]'$

Note: The credit contraction shock is a one standard deviation increase to credit standards cs_t. The dashed blue lines are 90% bootstrapped confidence intervals.

A.2 Industry-level Regressions

A.2.1 Markup Elasticities

I use the NBER-CES Manufacturing Industry Database to get estimates of the crucial parameter at a micro-level – the elasticity of markup with respect to competition. The data is annual from 1990-2006 at six-digit NAICS level. It is then merged with the number of establishments from the BLS QCEW database. This results in a panel database of 479 industries. The regression specification is as follows:

$$\Delta \ln \mu_{i,t} = \alpha_i + \varphi \mathbf{T}_{it} + \sum_{j=0}^{J} \beta_j \Delta \ln N_{i,t-j} + \sum_{k=1}^{K} \gamma_k \Delta \ln \mu_{i,t-k} + \Gamma S_{it} + \varepsilon_{it} \quad \text{(A.1)}$$

where $\mu_{i,t}$ is industry i's markup, $N_{i,t}$ is the number of establishments within industry i and $S_{i,t}$ is the value of shipments to control for cyclicality of markups. α_i are industry fixed effects and $\mathbf{T}_{i,t}$ is a vector of time controls. Lags of N_t and the dependant variable are added as it may take time for the effects of higher competition to be reflected in markups. The lag structure itself is chosen by statistical significance. For time controls, I use industry-specific linear time trends, because preliminary inspection of markups reveal that there is significant industry heterogeneity in their secular trends, perhaps due to the differing impacts of technological change to the industries during the sample period. Therefore, the variation used in the regression with linear trends is the within-industry movement of markups around the detrended series. Given that it is a dynamic panel, the well-known bias emerges when estimating with fixed effects. Therefore, I also run the regression using the Arrellano-Bond dynamic panel GMM.[1] The long-run elasticities of the various specifications and estimation methods are reported in Table A.1.

It is worth noting the probable endogeneity bias: higher markups would induce more entry. This would have an upward bias to the negative coefficients. Thus, the industry estimates here can be seen as the lower bound estimate of the magnitude of markup elasticities. That said, the

[1]There are less observations for Arellano-Bond as an extra lag is required to instrument the lagged dependant variables in the regression.

	OLS	OLS	OLS	A-B	A-B	A-B
LR Elasticity	-.32***	-0.20***	-.36***	-.54***	-.44***	-.56***
	(.063)	(.070)	(.099)	(.11)	(.11)	(.11)
J	4	4	4	4	4	4
K	1	1	1	1	1	1
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Controls	None	Agg. Trend	Ind. Trend	None	Agg. Trend	Ind. Trend
Observations	6069	6069	6069	5596	5596	5596
# of Industries	473	473	473	473	473	473

Clustered standard errors around industries
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.1. Estimates of Long-run Markup Elasticity

Note: The long-run elasticity is calculated as $\frac{\sum_{j=0}^{J}\beta_j}{1-\gamma_1}$.

endogeneity bias from reverse causality is likely to be minimal as current markups is unlikely to influence past entry. All estimates are statistically significant at 1% level. It is important to note that these elasticities are significantly higher than those suggested by translog preferences, of around -0.18 (Lewis and Stevens, 2012), compared to the baseline estimate of -0.56 that is used in the quantitative analysis. This demonstrates the importance of using a more flexible preference structure with the Kimball aggregator as described earlier.

A.2.2 Full Regressions

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) A-B	(5) A-B	(6) A-B
$\Delta ship_t$	0.358***	0.376***	0.362***	0.342***	0.363***	0.357***
	(0.021)	(0.022)	(0.027)	(0.020)	(0.023)	(0.021)
$\Delta ship_{t-1}$	0.013	0.029**	0.036*	-0.036*	-0.019	-0.028
	(0.015)	(0.015)	(0.019)	(0.020)	(0.021)	(0.018)
$\Delta ship_{t-2}$	-0.051***	-0.046***	-0.066***	-0.085***	-0.073***	-0.073***
	(0.010)	(0.010)	(0.016)	(0.013)	(0.014)	(0.013)
$\Delta ship_{t-3}$	-0.039***	-0.032**	-0.056***	-0.058***	-0.047***	-0.049***
	(0.013)	(0.013)	(0.019)	(0.014)	(0.014)	(0.012)
$\Delta ship_{t-4}$	-0.039***	-0.030***	-0.056***	-0.050***	-0.039***	-0.043***
	(0.010)	(0.010)	(0.016)	(0.011)	(0.012)	(0.010)
$\Delta ship_{t-5}$	-0.025*	-0.011	-0.039**	-0.031**	-0.019	-0.026*
	(0.014)	(0.014)	(0.018)	(0.014)	(0.015)	(0.014)
$\Delta ship_{t-6}$	0.005	0.017	-0.010	-0.006	0.005	-0.001
	(0.012)	(0.011)	(0.015)	(0.012)	(0.012)	(0.012)
ΔN_t	-0.093***	-0.074**	-0.106***	-0.133***	-0.123***	-0.137**
	(0.032)	(0.032)	(0.037)	(0.041)	(0.042)	(0.057)
ΔN_{t-1}	-0.033	-0.025	-0.063	-0.070	-0.062	-0.078*
	(0.042)	(0.042)	(0.046)	(0.047)	(0.045)	(0.045)
ΔN_{t-2}	-0.059	-0.034	-0.077*	-0.088**	-0.071*	-0.091**
	(0.039)	(0.039)	(0.044)	(0.042)	(0.042)	(0.042)
ΔN_{t-3}	-0.091**	-0.057	-0.095*	-0.114***	-0.094**	-0.115***
	(0.043)	(0.045)	(0.050)	(0.044)	(0.045)	(0.037)
ΔN_{t-4}	-0.081**	-0.032	-0.085*	-0.152***	-0.113**	-0.154***
	(0.035)	(0.036)	(0.044)	(0.048)	(0.050)	(0.057)
$\Delta \mu_{t-1}$	-0.104***	-0.124***	-0.185***	-0.037	-0.043*	-0.027
	(0.024)	(0.024)	(0.025)	(0.026)	(0.025)	(0.024)
year		0.003***			0.002**	
		(0.000)			(0.001)	
Constant	0.015***	-6.001***	-4.089***	0.013***	-3.378**	0.002*
	(0.001)	(0.850)	(1.280)	(0.001)	(1.326)	(0.001)
LR Elasticity	-0.32***	-0.20***	-0.36***	-0.54***	-0.44***	-0.56***
	(0.06)	(0.07)	(0.10)	(0.11)	(0.11)	(0.11)
Observations	6,069	6,069	6,069	5,596	5,596	5,596
R-squared	0.33	0.33	0.39			
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time Control	None	Agg. Trend	Ind. Trend	None	Agg. Trend	Ind. Trend

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.3 Derivation of Kimball Aggregator

A.3.1 Price Indices

The first order condition of the household's expenditure minimisation problem is:

$$p_t(\omega) = \frac{1}{\Lambda_t C_t}\Psi'\left(\frac{c_t(\omega)}{C_t}\right)$$

Relative demand or market share is:

$$\frac{c_t(\omega)}{C_t} = \Psi'^{-1}\left(p_t(\omega)\Lambda_t C_t\right)$$

where Λ_t is implicitly defined by substituting the demand function into the definitions of the aggregator:

$$\int_0^{N_t} \Psi\left(\Psi'^{-1}\left(p_t(\omega)C_t\Lambda_t\right)\right) d\omega = 1$$

and define some price index $\widetilde{P}_t \equiv 1/\Lambda_t C_t$ (note that this is not the conventional price index):

$$\int_0^{N_t} \Psi\left(\Psi'^{-1}\left(\frac{p_t(\omega)}{\widetilde{P}_t}\right)\right) d\omega = 1$$

The conventional (welfare-relevant) price index is instead:

$$P_t = \frac{1}{C_t}\int_0^{N_t} p_t(\omega)c_t(\omega)d\omega = \int_0^{N_t} p_t(\omega)\Psi'^{-1}\left(\frac{p_t(\omega)}{\widetilde{P}_t}\right) d\omega$$

Using the demand equation, the price index $\widetilde{P}_t$ is

$$\Rightarrow \widetilde{P}_t = \frac{p_t(\omega)}{\Psi'\left(\Psi^{-1}\left(\frac{1}{N_t}\right)\right)} \tag{A.2}$$

A.3.2 Elasticity of Demand

$$\theta(x_t(\omega)) \equiv -\frac{dc_t(\omega)}{dp_t(\omega)} \cdot \frac{p_t(\omega)}{c_t(\omega)} \Rightarrow \frac{1}{\theta(x_t(\omega))} = -\frac{d\ln p_t(\omega)}{dc_t(\omega)} \cdot c_t(\omega)$$

By assuming that each variety ω cannot affect the price index $\widetilde{P}_t$ and using equation (A.2):

$$\ln p_t(\omega) = \ln \widetilde{P}_t + \ln\left(\Psi'\left(\frac{c_t(\omega)}{C_t}\right)\right) \tag{A.3}$$

$$\frac{d\ln p_t(\omega)}{dc_t(\omega)} = \frac{\Psi''\left(\frac{c_t(\omega)}{C_t}\right)\frac{1}{C_t}}{\Psi'\left(\frac{c_t(\omega)}{C_t}\right)} \tag{A.4}$$

Using the definition $x_t \equiv c_t(\omega)/C_t$,

$$\frac{1}{\theta(x_t(\omega))} = -\frac{\Psi''(x_t(\omega))x_t(\omega)}{\Psi'(x_t(\omega))} \quad \Rightarrow \quad \theta(x_t) = -\frac{\Psi'(x_t)}{x_t\Psi''(x_t)}$$

Kimball assumes $\theta'(x_t) < 0$, and the number of competitors rise, market share falls $x(N_t) < 0$, as N rises then θ increases too.

A.3.3 Markup Elasticity

Define:

$$\varepsilon_\mu(x) \equiv \frac{\partial \ln \mu(x)}{\partial \ln x} = x\frac{\mu'(x)}{\mu(x)} \tag{A.5}$$

$$\frac{d\ln\mu}{d\ln N} = \frac{d\ln\mu}{d\ln x} \cdot \frac{d\ln x}{d\ln N} = \varepsilon_\mu(x) \cdot \frac{d\ln x}{d\ln N} \tag{A.6}$$

From equation (1.6):

$$\frac{1}{N} = \Psi(x) \quad \Rightarrow \quad \ln N = -\ln\left(\Psi(x)\right) \tag{A.7}$$

$$\frac{d\ln N}{dx} = -\frac{\Psi'(x)}{\Psi(x)} \tag{A.8}$$

$$\frac{d\ln N}{d\ln x} = -\frac{x\Psi'(x)}{\Psi(x)} = -N\cdot\Psi^{-1}(1/N)\Psi'\left(\Psi^{-1}(1/N)\right) \tag{A.9}$$

where the last line uses the definition of market share in symmetric equilibrium, equation (1.6) again. Therefore, the elasticity of markups w.r.t. varieties is:

$$\frac{d\ln\mu(x)}{d\ln N} = -\varepsilon_\mu(x)\cdot\frac{1}{N\cdot\Psi^{-1}(1/N)\Psi'\left(\Psi^{-1}(1/N)\right)} = -\varepsilon_\mu\cdot\frac{1}{N\cdot x\cdot\Psi'(x)} \tag{A.10}$$

A.3.4 Impulse Responses

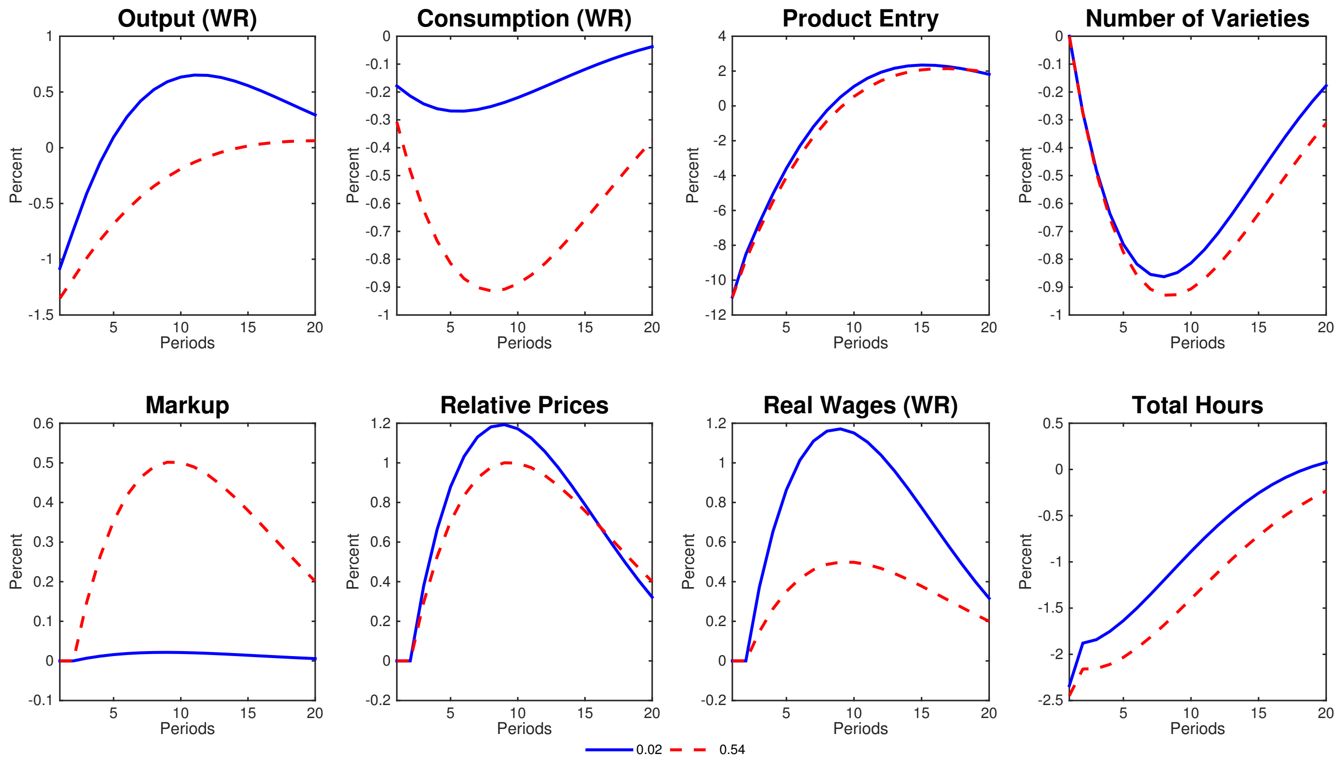


Figure A.7. Welfare-Relevant Real Variables

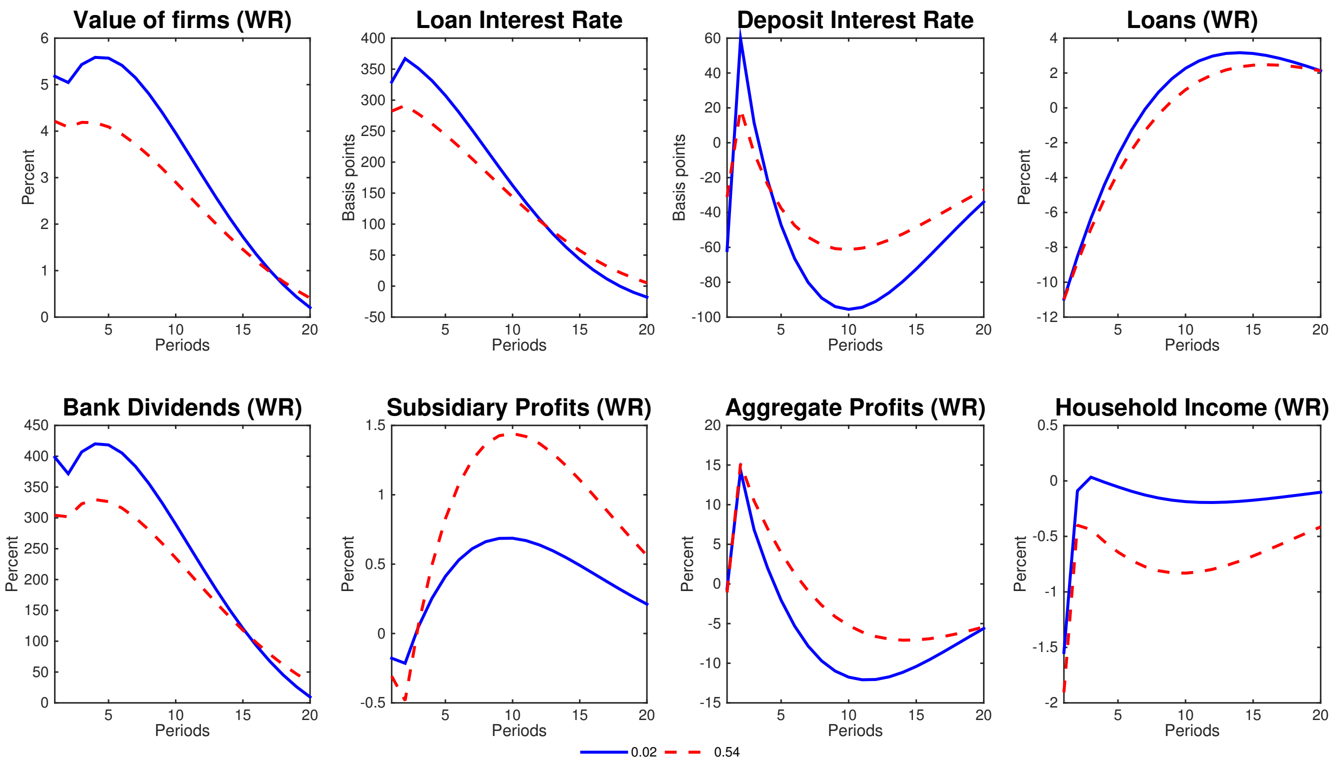


Figure A.8. Welfare-Relevant Financial Variables

Appendix B

Beyond Inventory Management: The Bullwhip Effect and the Great Moderation

B.1 Stylised Facts

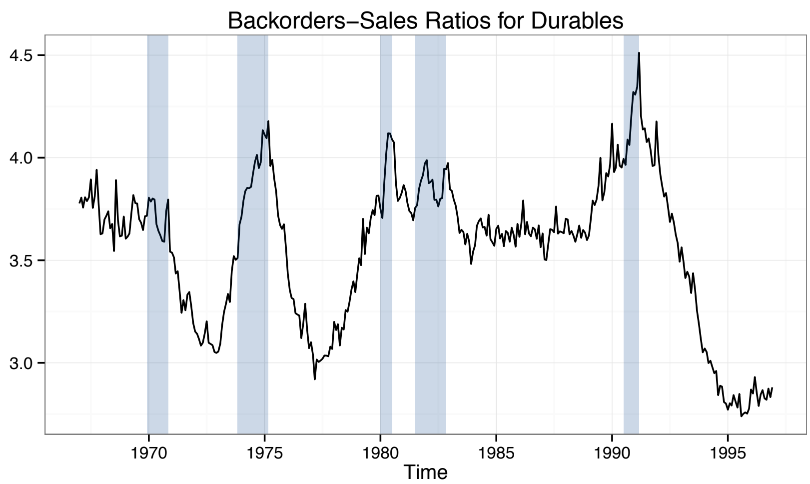
	Std. Dev		Shares	
	1960-1983	1984-2001	1960	2001
GDP (actual)	0.027	0.016		
Durables	0.084	0.053	0.18	0.18
Nondurables	0.030	0.018	0.31	0.19
Services	0.012	0.008	0.39	0.53
Structures	0.072	0.048	0.11	0.09

Table B.1. Stock and Watson (2003, Table 6) Counterfactuals

The counterfactual to approximate the role of durables in the overall Great Moderation is based on the following. Calculate the implied volatility of GDP by using the volatility and weight of each sector s, but omit the covariance terms. $\sqrt{\sum_s \omega_{s,HV}^2 \sigma_{s,HV}^2} = 0.020$ and $\sqrt{\sum_s \omega_{s,LV}^2 \sigma_{s,LV}^2} = 0.0118$.

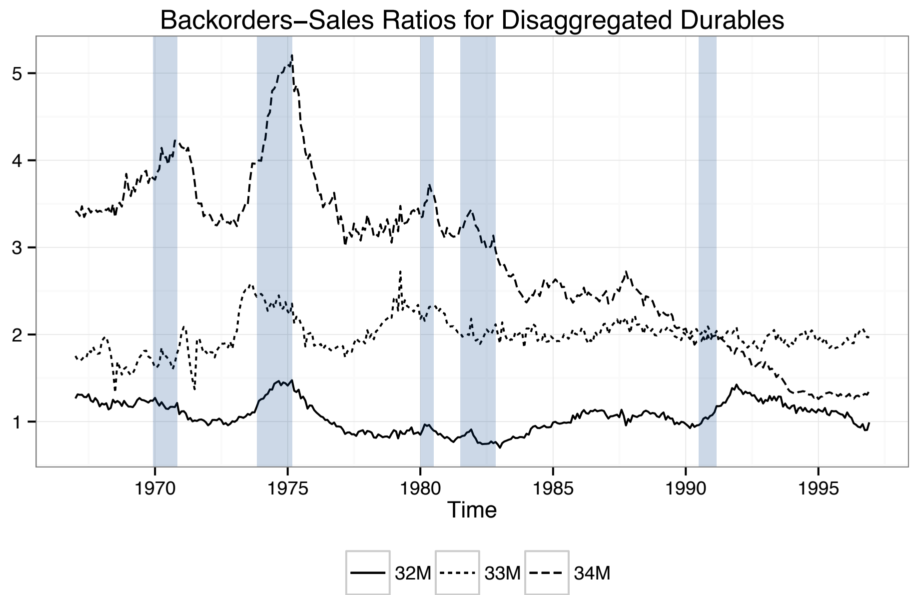
This results in a ratio 0.0118/0.020 = 0.59, or a 40% reduction in volatility. Coincidentally, the ratio of *actual* GDP volatilities is also 0.016/0.027 = 0.59, meaning that the effects of the covariances cancel out. Or equivalently, the ratio between the actual and implied volatility is constant for the two periods (0.027/0.020 = 1.35 and 0.16/0.118 = 1.35).

To get an approximation of the effect of durables, substitute the *LV* volatility of durables, while keeping all other industries in the *HV* period, resulting in an implied volatility of 0.0166. The ratio from the implied volatility in the *HV* period is (0.0162/0.020 = 0.81). Thus we conclude that durables account for approximately half of the Great Moderation. In comparison, if a similar counterfactual is performed on non-durables (a much bigger sector) implies a volatility of 0.018, or only a 10% reduction in overall volatility, as opposed to the 20% of durables.



Shaded areas are NBER-dated recessions

Figure B.1. Backorders to Shipments Ratio for All Durables Industries



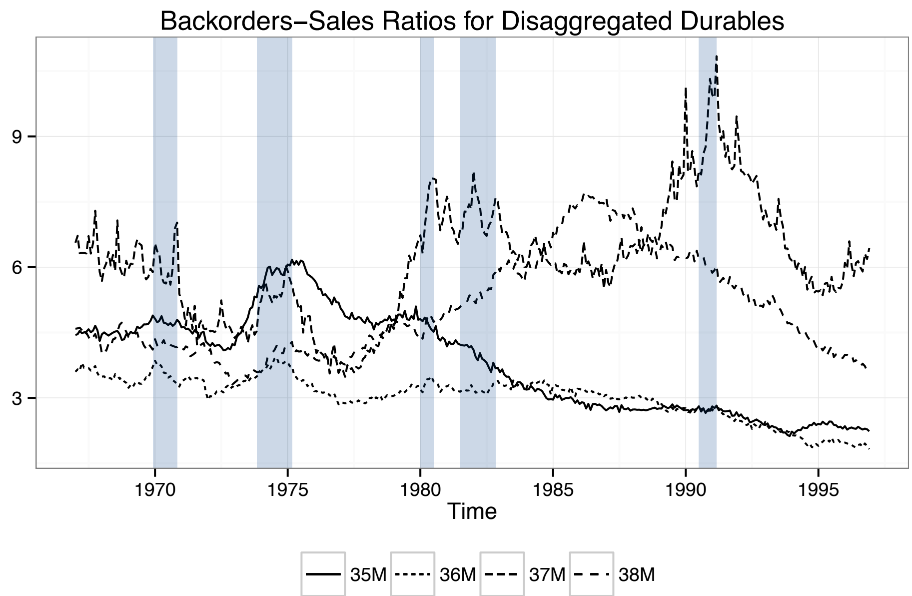


Figure B.2. Disaggregated Backorders to Shipments Ratio

Note: SIC codes: 32M – Stone, Clay and Glass, 33M – Primary metals, 34M – Fabricated metals, 35M – Industrial machinery and equipment, 36M – Electronic and other electrical equipment, 37M – Transportation equipment, 38M – Instruments and related products.

Counterfactuals	*Relative RMSE* $[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{HV}]$ Practices	$[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{LV}]$ Macro	$[\mathbf{\Gamma}_{LV}, \mathbf{\Lambda}_{LV}]$ Total
New Orders o_t	0.81	0.87	0.57
Backorders u_t	1.01	0.90	0.80
Relative price $\overline{p}_t$	1.58	0.65	1.13
M&S Inventory m_t	0.66	0.92	0.70
FG Inventory h_t	0.56	0.72	0.50

Table B.3. 60-month RMSE counterfactuals – business practices vs. macro (non-durables)

Note: RMSEs are relative to the *HV* micro and macro parameters/shocks, ie. $[\mathbf{\Gamma}_{HV}, \mathbf{\Lambda}_{HV}]$.

Counterfactuals	*Relative RMSE* Within Industry LV	All other parameters LV	All parameters LV
New Orders o_t	0.82	0.80	0.73
Backorders u_t	2.07	0.91	0.84
Relative price $\overline{p}_t$	3.09	0.36	0.79
M&S Inventory m_t	5.02	1.41	1.54
FG Inventory h_t	1.95	3.18	1.69

Table B.2. 60-month counterfactuals of the within industry parameters, given Σ_{HV}

Note: RMSEs are relative to the *HV* micro and macro parameters/shocks

B.2 Non-Durables Results

Counterfactuals	*Relative RMSE* $\left[\Theta_i^{HV}, \Sigma_i^{LV}\right]$ Shocks	$\left[\Theta_i^{LV}, \Sigma_i^{HV}\right]$ Structure	$\left[\Theta_i^{LV}, \Sigma_i^{LV}\right]$ Total
New Orders o_t	0.86	0.60	0.57
Backorders u_t	0.89	0.92	0.80
Relative price $\overline{p}_t$	0.97	1.30	1.13
M&S Inventory m_t	0.99	0.84	0.70
FG Inventory h_t	1.01	0.52	0.50

Table B.4. 60-month RMSE counterfactuals – structure vs. shocks (non-durables)

Note: RMSEs are relative to the *HV* micro and macro parameters/shocks, ie. $[\mathbf{\Theta}_{HV}, \mathbf{\Sigma}_{HV}]$.

	RMSE	Forecast Variance Decomposition (%) Own	o_{it}	u_{it}	Other Industry	Aggregate
High Volatility						
New Orders o_{it}	0.52		4.68	0.46	1.43	93.43
Backorders u_{it}	1.99		0.02	2.02	1.74	96.23
Relative price $\overline{p}_{it}$	0.51	5.81	0.61	0.09	1.40	92.08
M&S Inventory m_{it}	0.57	2.35	0.27	0.67	5.62	91.08
FG Inventory h_{it}	0.56	11.59	0.17	0.53	1.22	86.49
Low Volatility						
New Orders o_{it}	0.30		8.67	0.16	2.30	88.87
Backorders u_{it}	1.60		0.16	1.67	17.10	81.07
Relative price $\overline{p}_{it}$	0.57	21.11	0.04	0.43	2.41	76.02
M&S Inventory m_{it}	0.40	7.74	0.29	0.21	7.65	84.10
FG Inventory h_{it}	0.28	16.90	0.18	0.22	8.61	74.09

Table B.5. Forecast Error Variance Decomposition

Note: The second column is the percentage of the forecast error variance that can be attributed to the the shock of the variable itself. The second , third and fourth columns is the FEVD to new orders and backorder shocks, and all other industry-level variables, respectively. The last column is the FEVD attributed to the macro block of variables.

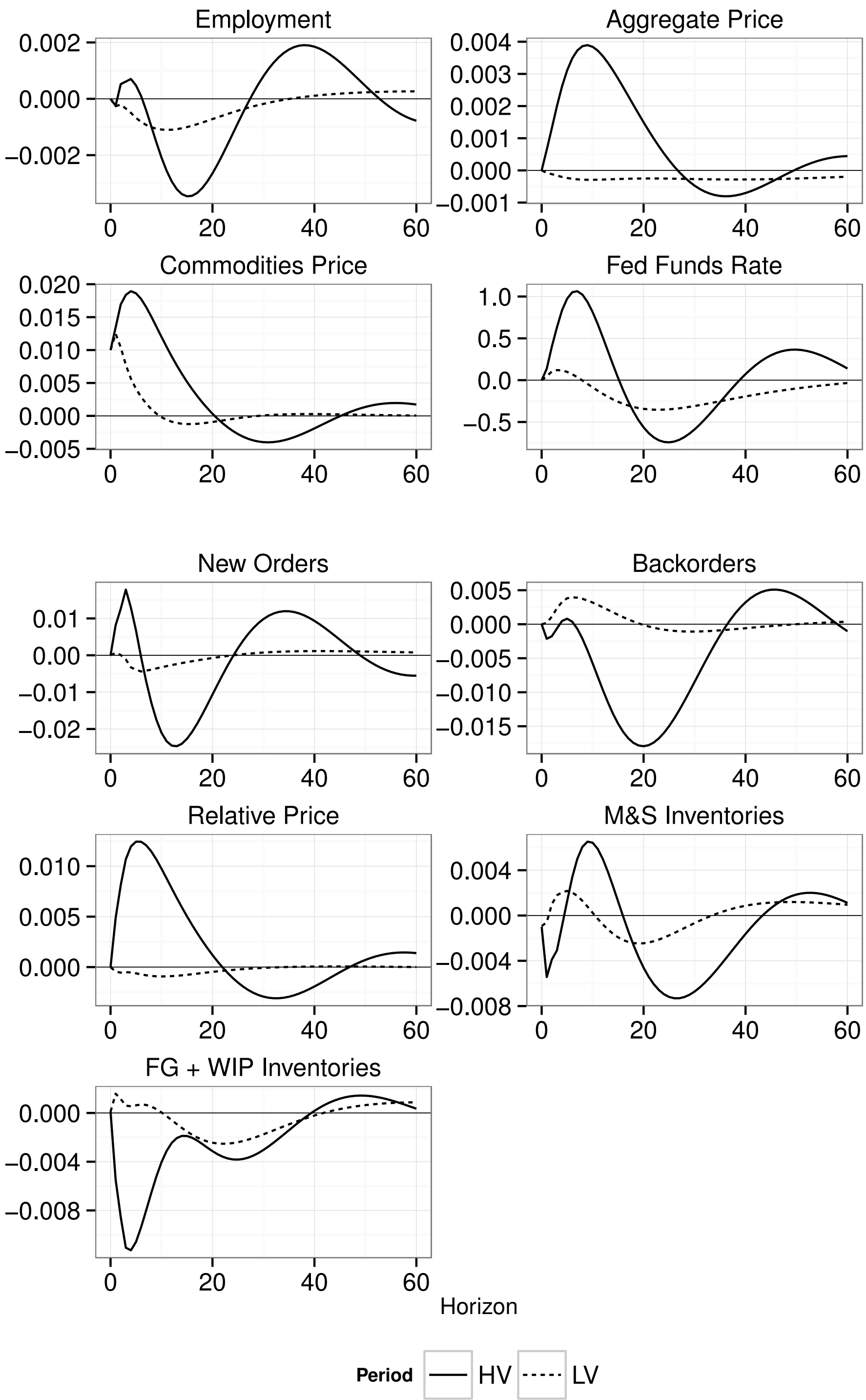


Figure B.3. Impulse Responses to a 1% increase in commodities prices

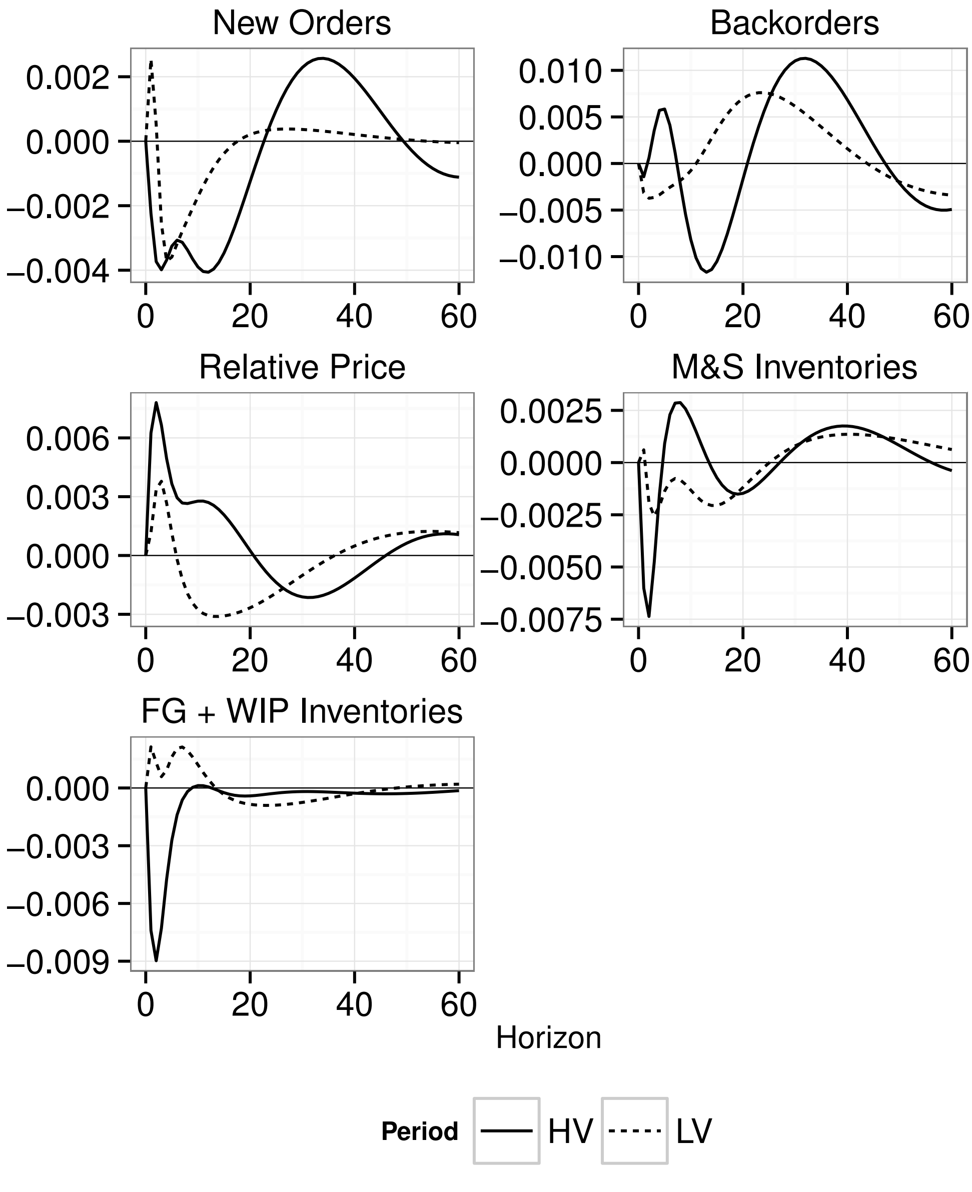


Figure B.4. Non-durables Impulse Responses to a 100 bps Fed Funds Rate Increase

Appendix C

Leaning Against the Wind and Policy Tradeoffs

C.1 Model with financial frictions à la Gertler and Karadi (2011)

$$\hat{u}_{c,t} = -\frac{1}{1-h}\hat{c}_t + \frac{h}{1-h}\hat{c}_{t-1} \tag{C.1}$$

$$\hat{\Lambda}_t = \hat{\psi}_t - \hat{\psi}_{t-1} + \hat{u}_{c,t} - \hat{u}_{c,t-1} \tag{C.2}$$

$$\hat{\lambda}_t = \frac{\theta}{\theta - \overline{\mu}}\hat{\mu}_t \tag{C.3}$$

$$(\overline{\nu} - \theta)\overline{N}\hat{n}_t + \overline{\nu}\overline{N}(\hat{\nu}_t - \hat{q}_t) = \overline{D}(\theta - \overline{\mu})\hat{d}_t - \overline{\mu}\overline{D}\hat{\mu}_t \tag{C.4}$$

$$\hat{\mu}_t = \hat{\Lambda}_{t+1} + \hat{\Omega}_{t+1} + (\overline{R}_s\hat{r}_{s,t+1} - \overline{R}\hat{r}_t)/(\overline{R}_s - \overline{R}) \tag{C.5}$$

$$\hat{\nu}_t - \hat{q}_t = \hat{\Lambda}_{t+1} + \hat{\Omega}_{t+1} + \hat{r}_{s,t+1} \tag{C.6}$$

$$\overline{\Omega}\hat{\Omega}_t = \sigma\overline{\nu}(1 + \overline{\lambda})(\hat{\nu}_t - \hat{q}_t) + \sigma\overline{\lambda}(\overline{\nu} - \theta)\hat{\lambda}_t \tag{C.7}$$

$$\hat{n}_t = (\sigma + \xi)(\overline{S}/\overline{N})\overline{R}_s(\hat{q}_{t-1} + \hat{s}_{t-1} + \hat{r}_{s,t}) - \sigma(\overline{D}/\overline{N})\overline{R}(\hat{r}_{t-1} + \hat{d}_{t-1}) \tag{C.8}$$

$$\overline{D}\hat{d}_t = \overline{S}(\hat{q}_t + \hat{s}_t) - \overline{N}\hat{n}_t \tag{C.9}$$

$$-\hat{\Lambda}_{t+1} = \hat{r}_t \tag{C.10}$$

$$\hat{w}_t + \hat{u}_{c,t} = \hat{\psi}^{\ell}_t + \varphi\hat{l}_t \tag{C.11}$$

$$\hat{y}_t = \hat{a}_t + \alpha\hat{k}_{t-1} + (1-\alpha)\hat{l}_t \tag{C.12}$$

$$\hat{z}_t = \hat{\mathrm{mc}}_t + \hat{y}_t - \hat{k}_{t-1} \tag{C.13}$$

$$\hat{w}_t = \hat{\mathrm{mc}}_t + \hat{y}_t - \hat{l}_t \tag{C.14}$$

$$\overline{R}_s(\hat{q}_{t-1} + \hat{r}_{s,t}) = \overline{Z}\hat{z}_t + (1-\delta)\hat{q}_t \tag{C.15}$$

$$\hat{q}_t = \kappa(\hat{i}_t - \hat{i}_{t-1}) - \beta\kappa(\hat{i}_{t+1} - \hat{i}_t) \tag{C.16}$$

$$\hat{\Gamma}_{1,t} = (1-\gamma\beta)(\hat{\mathrm{mc}}_t + \hat{y}_t) + \gamma\beta(\hat{\Lambda}_{t+1} + \varepsilon\hat{\pi}_{t+1} - \iota\varepsilon\hat{\pi}_t + \hat{\Gamma}_{1,t+1}) \tag{C.17}$$

$$\hat{\Gamma}_{2,t} = (1-\gamma\beta)\hat{y}_t + \gamma\beta[\hat{\Lambda}_{t+1} + (\varepsilon-1)\hat{\pi}_{t+1} - \iota(\varepsilon-1)\hat{\pi}_t + \hat{\Gamma}_{2,t+1}] \tag{C.18}$$

$$\gamma\hat{\pi}_t - \gamma\iota\hat{\pi}_{t-1} = (1-\gamma)\hat{\pi}^*_t \tag{C.19}$$

$$\hat{\pi}^*_t = \hat{\psi}^{\mathcal{M}}_t + \hat{\Gamma}_{1,t} - \hat{\Gamma}_{2,t} \tag{C.20}$$

$$\hat{f}_t = \rho\hat{f}_{t-1} + (1-\rho)[\phi_\pi\hat{\pi}_t + \phi_y\hat{y}_t] \tag{C.21}$$

$$\hat{f}_t = \hat{r}_t + \hat{\pi}_{t+1} \tag{C.22}$$

$$\hat{k}_t = (1-\delta)\hat{k}_{t-1} + \delta\hat{i}_t \tag{C.23}$$

$$\hat{y}_t = (\overline{C}/\overline{Y})\hat{c}_t + (\overline{I}/\overline{Y})\hat{i}_t + (\overline{G}/\overline{Y})\hat{g}_t \tag{C.24}$$

$$\hat{k}_t = \hat{s}_t \tag{C.25}$$

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